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Faculté des Sciences Economiques et de Gestion

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THESE

de Doctorat de Sciences Economiques

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# Une investigation expérimentale des capacités éductives des agents dans des situations de feedback négatif

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# An experimental investigation of the eductive abilities of the agents in negative feedback environments

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*A ma fille Mara,*
*à mon époux Virgil.*
*A ma sœur Dana.*
*A mes parents Gherghina et Ioan.*

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# Short Contents

# Introduction Générale

*"Professional investment may be likened to those newspaper competitions in which the competitors have to pick out the six prettiest faces from a hundred photographs, the prize being awarded to the competitor whose choice most nearly corresponds to the average preferences of the competitors as a whole; so that each competitor has to pick, not those faces which he himself finds prettiest, but those which he thinks likeliest to catch the fancy of the other competitors, all of whom are looking at the problem from the same point of view. It is not a case of choosing those which, to the best of one's judgment, are really the prettiest, nor even those which the average opinion genuinely thinks the prettiest. We have reached the third degree where we devote our intelligence to anticipating what the average opinion expects the average opinion to be. And there are some, I believe, who practice the fourth, fifth and higher degrees."*

*(Keynes, 1936)*

En absence d'un commissaire-priseur, l'obtention d'un prix d'équilibre sur un marché concurrentiel reste en partie énigmatique. Afin de résoudre un tel problème, la recherche économique avait traditionnellement opté pour le choix de peupler ses modèles d'*homo(s) oeconomicus*. Doté de rationalité illimitée, homo oeconomicus était un agent économique standardisé, capable de comprendre parfaitement son environnement (sur lequel de plus il avait le plus souvent une information parfaite et complète) et de décider de manière instantanée et automatique des actions qu'il devait prendre dans des situations complexes.

Cependant, avec la redécouverte de l'intérêt que pourrait avoir l'introduction en économie d'éléments psychologiques (entre autres apports contemporains), les acteurs économiques sont redevenus multiples et les agents ont regagné leur statut de *sapiens*. Lorsqu'en 1936, Keynes compare les activités des marchés financiers à des concours de beauté, il fait état dans sa métaphore de cette multiplicité des agents, résultant en particulier de leurs différentes capacités *cognitives* ou de raisonnement. Imaginons une situation dans laquelle les fondamentaux économiques sont publiquement révélés, de manière à ce que tous les agents participants aient une information complète, parfaite et symétrique sur leur environnement. *Toutes choses* (pourtant) *égales par ailleurs*, les agents intervenant dans ce type d'environnement ne sont pas symétriques, parce qu'ils ont des capacités cognitives différentes. Ainsi, chaque agent traite l'information qu'il reçoit de manière différente, selon sa capacité de raisonnement. L'existence de cette multitude d'agents implique une incertitude comportementale à laquelle les individus doivent faire face lorsqu'ils prennent leurs décisions. En l'absence de certitude sur les actions de leurs adversaires, les agents doivent donc former des croyances sur leurs stratégies avant de prendre leurs décisions. L'établissement d'un prix d'équilibre résulte par la suite d'une coordination des croyances d'agents différents.

Une partie importante de la recherche en économie est consacrée à la question de l'utilisation par les agents de l'information disponible pour former leurs croyances, pour fournir des prévisions et pour prendre des décisions basées sur cette activité. Les premières tentatives d'expliquer la formation des croyances se basaient sur des règles simples comme les anticipations naïves ou adaptatives. Depuis, des évidences empiriques ont mis en avant le fait que, premièrement, les différences des agents devaient se retrouver dans la multiplicité des règles de prévision et deuxièmement, des règles de raisonnement plus complexes devaient être considérées, puisque, comme souligné par Keynes, certains agents utilisent des stratégies gagnantes. Ce point marque un retour au concept de rationalité, mais comme *résultante d'un processus* de raisonnement qui peut s'avérer complexe. Muth (1961), par l'exemple, a fait l'hypothèse que les agents utilisent toute l'information disponible pour mettre en place des anticipations *rationnelles* qui les conduisent à l'équilibre à travers un *processus* de raisonnement, différent des réponses quasi-automatiques de l'homo oeconomicus. Cette nouvelle règle exige que les agents possèdent une connaissance commune sur l'environnement et l'utilisent sans commettre des erreurs systématiques et sans avoir bénéfice à dévier ; ainsi, les agents feraient des bonnes prévisions parce que cela serait dans leur propre intérêt. Guesnerie (1992) suggère une interprétation duale de cette hypothèse : il est juste de supposer qu'il est dans l'intérêt des agents de faire des prévisions correctes ; il est erroné de supposer que la coordination parfaite est le résultat nécessaire d'une agrégation d'efforts d'optimisation isolés. Une bonne prévision doit tenir compte de la possibilité de prévisions erronées de la part des autres agents. Par conséquent nous devrions interpréter l'hypothèse d'anticipations rationnelles comme une conséquence de la rationalité et de la connaissance commune de la rationalité.

La rationalité d'agents différents se décline-t-elle en *rationalités* différentes ? Une approche en termes de *degrés de rationalité* différents ou de *profondeurs de rationalité* différentes rencontre la difficulté de la conceptualisation et la transformation en connaissance commune de cette distribution de rationalités différentes dans une population d'agents. Les capacités de raisonnement différentes des agents sont en particulier associées à leurs coûts (cognitifs) de traitement de l'information ; chaque agent réalise donc un arbitrage avantages-coûts du raisonnement qui détermine les limites du raisonnement mis en œuvre ; ces limites doivent être prises en compte dans les conditions assumées dans l'hypothèse des anticipations rationnelles.

Notre thèse se concentre sur la manière dont les agents comprennent, traitent et assimilent l'information disponible en fonction de leurs capacités de raisonnement. Nous sommes intéressés en particulier par la manière dont, sur la base de ce raisonnement, ils forment des croyances qui s'articulent. Nous évaluons ces croyances parce qu'elles révèlent les profils cognitifs des agents. Ainsi, nous nous intéressons à l'étude des processus qui conduisent les agents à choisir des stratégies gagnantes et à éliminer les stratégies qui ne leur permettraient pas de maximiser leurs bénéfices (stratégies dominées). Comme les agents sont susceptibles d'entreprendre ce type d'action simultanément, les stratégies disponibles sont continuellement mises à jour, chaque agent déployant ses capacités de raisonnement en parallèle, tout en supposant une distribution de profils pour ses adversaires. Il est donc probable que les processus d'élimination des stratégies dominées soient mis à l'œuvre de manière répetée, parce que chaque agent doit tenir compte de la nouvelle structure de l'environnement et des croyances des autres (jusqu'à la limite de sa capacité cognitive) avant de former une prévision : ainsi le processus de raisonnement doit-il être vu comme un processus itératif.

Le traitement de l'information, la formation de croyances et finalement la prise de décision impliquent l'exploitation de ses capacités cognitives, qui est une activité mentale complexe, basée sur des opérateurs logiques croisés (l'anticipation des anticipations des autres), appelée, depuis Binmore (1987), *éduction*. Quel est le mécanisme de ce type de raisonnement ? **C'est**

**la question à laquelle notre thèse s'attache à répondre à travers des expériences**. Basé sur des inférences logiques, le *raisonnement éductif* ou *divinatoire* se déroule en étapes et son succès dans une population d'agents dépend d'une introspection collective. L'équilibre d'anticipations rationnelles correspond à la mise en œuvre d'un nombre infini d'étapes de sophistication, à un raisonnement divinatoire collectif mené à l'infini. L'hypothèse plus probable est de considérer seulement un nombre fini d'étapes mises en place. Chaque étape supplémentaire accroît la sophistication du raisonnement et détermine la profondeur de raisonnement d'un agent, qui définit son type.

Ainsi le type d'un agent correspond-il à la dernière étape de raisonnement divinatoire qu'il met en place avant de prendre une décision. La règle d'arrêt du processus de sophistication est déterminée de manière involontaire ou volontaire ; dans le premier cas, la dernière étape du processus de raisonnement divinatoire correspond à la capacité cognitive de l'agent ; dans l'autre cas, la dernière étape de sophistication correspond au moment où l'agent est capable de transformer ses croyances réflectives (qui sont le résultat des étapes de sophistication) en croyances intuitives (qui ne sont le résultat d'aucun calcul ni inférence, et ne réclament aucune explication) : à partir de ce moment-là, il est capable soit de "sauter" directement à l'équilibre (s'il anticipe que ses adversaires ont des capacités éductives comparables à la sienne), soit d'être le gagnant de la situation (s'il perçoit ses adversaires comme étant dotés de capacités de sophistication inférieures).

Comme ce type de raisonnement est difficile à mettre en œuvre, existe-t-il des facteurs susceptibles de le favoriser ? En particulier, le raisonnement divinatoire pourrait mieux aboutir dans des situations stabilisatrices. Tout processus est caractérisé par un sentier d'évolution théorique et des oscillations qui peuvent le faire dévier. Dans une situation stabilisatrice, un processus est soumis à des forces qui le ramènent dans son sentier d'évolution et qui tempèrent les déviations. Des signaux de sens contraire aident à mieux cerner l'équilibre et un processus de raisonnement de type éductif est favorisé. L'effet de stabilisation est dû au fait que n'importe quelle déviation dans une direction sera partiellement compensée par une déviation dans l'autre direction. Pour que cela soit possible, des forces substituables doivent intervenir dans l'environnement. Un tel environnement correspond par exemple à une situation de vente de produits agricoles : si tous les agents produisent beaucoup en pensant que le prix sera élevé, le prix va s'effondrer sous l'effet d'un excès d'offre. C'est une situation typique de feedback négatif. Ainsi notre thèse est focalisée sur la mise en place du raisonnement divinatoire dans cet environnement particulier : **nous mesurons les capacités éductives des agents dans des situations de feedback négatif.**

L'économie expérimentale offre un cadre propice pour le test de ce type de raisonnement et pour la mise en place d'un environnement contrôlé, non-bruité, de feedback négatif. Bien qu'ayant lieu dans la tête des agents, le processus éductif peut être révélé par la mise en place d'expériences. Nous testons expérimentalement la mise en place des étapes du raisonnement éductif dans deux types de situations de feedback négatif : **nous introduisons une nouvelle variante de jeu du concours de beauté, à feedback négatif** et nous l'appliquons à un marché de type cobweb (le jeu du concours de beauté à feedback négatif est en fait le squelette du marché cobweb).

Les expériences sur les jeux du concours de beauté sont devenues populaires en économie, depuis les travaux de Nagel (1995), afin d'étudier différents modèles de raisonnement. Le succès de ces expériences se fonde sur le fait qu'elles puissent répondre au besoin de dissocier une activité mentale éductive d'une logique évolutive. Les arguments évolutifs, offerts par la répétition de la situation, sont inhérents aux expériences où des sujets sont invités à prendre des décisions analogues de manière répétée. Même si les conditions du succès instantané du raisonnement éductif et de la convergence évolutive asymptotique sont identiques (les deux processus ont les mêmes cartes d'étapes), le raisonnement éductif peut être identifié dans la classification des réponses initiales. Nous y introduisons le feedback négatif, ce qui nous permet de faire le lien avec les travaux en psychologie, en localisant l'équilibre du jeu à l'intérieur et en modifiant l'allure du processus de raisonnement. Ceci accroît les chances d'atteindre l'équilibre par rapport à un jeu standard par un balayage répété et donc une meilleure localisation de l'équilibre du jeu.

Sur les marchés, des situations de feedback négatif sont formalisées dans les modèles cobweb. Le cobweb fait partie de la famille des modèles qui supposent un retard entre le moment où la décision de production est prise et le moment où la production est effectivement vendue sur le marché et qui formalisent des marchés de produits non-stockables. A cause de cet intervalle de temps, les agents doivent former des croyances sur les stratégies des autres avant de prendre leurs décisions. Ces modèles prennent en compte des environnements économiques tels l'agriculture, où l'approvisionnement doit être déterminé quelques mois à l'avance. Ce retard force les fournisseurs (les producteurs) à prévoir les prix de la période suivante avant que le prix réel soit effectivement connu. Ainsi, avant de décider de la quantité qui sera fournie au marché, les producteurs doivent former des anticipations sur le prix futur et baser leurs décisions de production sur ces prévisions : puisque cela prend une période de temps pour produire le bien, la décision de production dépendra de leur anticipation du prix qui sera établi sur le marché. Ainsi, le marché est déterminé principalement par les prévisions des prix et des décisions de production résultantes, plutôt que par le côté de la demande. Des prévisions de prix croissants mènent à une hausse de la production, à un excès d'offre donc à des prix inférieurs, ce qui caractérise un feedback négatif. En testant ce marché, nous étudions le raisonnement éductif contingent à plusieurs configurations de marché.

Pour synthétiser, l'investigation de la mise en place du raisonnement éductif est le fil conducteur de notre thèse. Nous construisons cette thèse autour de trois questions : quel est le mécanisme par lequel ce type de raisonnement se met en place ? Existe-t-il des situations dans lesquelles il est plus probable que le raisonnement éductif aboutisse ? Dans ce type de situations, y a-t-il des conditions sous lesquelles les performances de ce type de raisonnement s'améliorent ? Nous identifions les environnements de feedback négatif comme des situations stabilisatrices pour le raisonnement éductif ; la répétition, l'élicitation et la circularité comme des conditions de son succès. **Notre thèse montre que, dans des situations de feedback négatif, les croyances réflectives se transforment en croyances intuitives plus rapidement, parce qu'à travers un raisonnement éductif l'équilibre est scanné de manière répétée et l'information utile est accrue. C'est la raison pour laquelle les marchés qui ont une structure de feedback négatif sont stables et les agents qui y interviennent ont des croyances coordonnées.**

Ainsi le premier chapitre constitue une introduction non technique dans le sujet du raisonnement éductif en situation de feedback négatif. La première partie formalise ces concepts dans des jeux du concours de beauté et la deuxième partie en montre l'application sur les marchés linéaires de type cobweb. Les premiers chapitres de chaque partie (chapitre 2 et chapitre 5) font des présentations détaillées du jeu du concours de beauté à feedback négatif que nous introduisons et du modèle cobweb ; nous intégrons aussi dans ces chapitres des revues de la littérature expérimentale antérieure qui est relative à nos travaux. Cependant, les principaux éléments théoriques sont repris dans chacun des autres chapitres, ainsi les chapitres 3, 4, 6, 7 et 8, qui présentent nos travaux expérimentaux, peuvent être lus de manière indépendante (les chapitres 1, 2 et 5 fournissant les détails techniques ou argumentaires).

La thèse comporte huit chapitres. Dans le **chapitre 1** nous montrons comment est mis en place le processus de formation des croyances que les agents doivent entreprendre afin de répondre aux incertitudes comportementales auxquelles ils font face. Ce processus dépend des caractéristiques de la situation ; dans des situations-limites les agents peuvent soit se baser sur un point focal, soit mettre en œuvre un processus de raisonnement complexe dans lequel ils "anticipent les anticipations des autres"(Binmore, 1987), i.e. *le raisonnement éductif* ; des situations intermédiaires sont possibles. Ainsi, ce chapitre introduit-il le raisonnement éductif, auquel nous nous intéresserons pour la suite de cette thèse. Comme ce type de raisonnement résulte de la mise en place de plusieurs étapes successives, il est probable que le processus ne soit pas conduit jusqu'à l'infini, soit involontairement, parce que les agents ont des capacités éductives limitées, soit volontairement, parce qu'ils s'imposent à eux-mêmes une limite en estimant que leurs opposants auront des limites inférieures ou à la suite d'une analyse en termes de coûts de l'effort. Le chapitre retrace dans une première partie la mise en place de l'hypothèse d'anticipations rationnelles, la définition de la notion de raisonnement éductif avec ses étapes (chaque étape franchie correspond à un degré de raisonnement et détermine un type d'agent) ; la distinction entre raisonnement éductif et évolutif ; les relations avec la connaissance commune ; le rôle de l'analyse coût-bénéfices dans le traitement de l'information. Dans une seconde partie les systèmes à feedback négatif sont décrits : ils correspondent à des situations dans lesquelles toutes deux actions successives ont des conséquences opposées ; ce sont des situations de substituabilités stratégiques, et dans lesquelles le raisonnement éductif est favorisé et stabilisé. Nous y introduisons une discussion sur le moment qui détermine la règle d'arrêt du raisonnement éductif, qui correspond au moment où les croyances réflectives deviennent intuitives (Sperber, 1997). Nous montrons que ce moment découle de l'architecture de la communication verbale et est donc "naturel" dans des situations de feedback négatif ; cela est en plus une conséquence de la manière dont on fait usage des nombres (Dehaene, 1993).

La suite de la thèse se décompose en deux parties qui formalisent les discussions introductives du premier chapitre. La **première partie** fait état d'une approche de la notion de raisonnement éductif en situation de feedback négatif par les jeux du concours de beauté : nous proposons une nouvelle variante de ces jeux, que nous présentons puis testons expérimentalement. Le **chapitre 2** introduit ainsi les jeux du concours de beauté à feedback négatif. Dans ces jeux, les participants doivent choisir un nombre entre 0 et 100 et le gagnant est la personne qui est la plus proche de 100 – *p*moyenne de tous les nombres choisis dans un groupe. Nous caractérisons mathématiquement ces jeux : nous montrons en particulier qu'ils sont isomorphes aux jeux du concours de beauté classiques, mais ont un équilibre intérieur qui est atteint par un processus de convergence oscillatoire à amplitude décroissante, ce qui implique une meilleure localisation de l'équilibre car une meilleure exploitation de l'intervalle de choix. En outre, ces jeux évitent des phénomènes d'ancrage et stabilisent les croyances. Le chapitre fait aussi une revue de la littérature sur les jeux du concours de beauté classiques, afin de présenter les différentes modifications et analyses qui ont été apportées à ces jeux, et démontre l'équivalence entre ces jeux et les marchés de produits périssables de type cobweb.

Dans le **chapitre 3**, une expérience à une seule période est mise en place avec 324 sujets divisés en groupes, pour le paramètre $p = ⅔$, afin d'essayer d'établir une typologie des participants en fonction de leur degré de raisonnement. Nos résultats montrent que : *i)* les choix sont concentrés autour des valeurs correspondant aux différentes étapes de raisonnement éductif ; *ii)* dans un modèle de hiérarchie cognitive, les participants correspondent à des joueurs de type 2 (qui estiment qu'ils sont face à des joueurs qui soit choisissent au hasard, soit estiment que les autres choisissent au hasard et répondent à cette estimation) ; *iii)* la vitesse de convergence empirique du processus de raisonnement est plus rapide que dans les jeux à feedback positif ; *iv)* la répétition simulée du jeu à partir de la configuration initiale mènerait à l'équilibre plus rapidement que dans le jeu classique.

Afin de vérifier le résultat de notre simulation et pour prendre en compte les effets de la répétition du jeu sur les choix initiaux, dans le **chapitre 4**, des jeux du concours de beauté à feedback négatif à plusieurs périodes sont testés. Le chapitre commence par une partie théorique dans laquelle nous formalisons le processus de traitement de l'information en prenant en compte l'approche de Shannon (l'entropie) et les travaux de Dehaene (1993) sur la perception des nombres (l'effet SNARC). Nous montrons que l'information utile est plus grande dans nos jeux et qu'il existe un point qui détermine la transformation des croyances réflectives en croyances intuitives, qui dépend du paramètre de convergence du jeu, $p$ : plus il est petit, moins on a besoin d'étapes de raisonnement pour atteindre l'équilibre. Nous testons deux valeurs de $p$, ¼ et ⅔, avec 128 sujets. Nos résultats montrent que : *i)* les réponses peuvent être attribuées à des joueurs de type 2 ; *ii)* les choix sont concentrés autour de l'équilibre ; *iii)* trois étapes de raisonnement suffiraient pour atteindre le point où les croyances réflectives se transforment en croyances intuitives.

La **deuxième partie** de la thèse correspond à une approche du raisonnement éductif dans des situations simples de marché de type cobweb. Ces situations réelles sont une application directe des jeux du concours de beauté à feedback négatif. Ainsi, le **chapitre 5** présente le modèle cobweb linéaire ; ce modèle décrit des situations de production de biens agricoles dans lesquelles les décisions de production doivent être prises une période avant la mise en vente sur le marché, et dans lesquelles les producteurs forment des anticipations. Les conditions de convergence des anticipations sont présentées, ainsi que l'équivalence avec les jeux précédents. Nous y présentons aussi le déroulement du raisonnement éductif et différents modèles de rationalité limitée appliqués à ce type de marchés, ainsi que la littérature expérimentale développée sur les marchés de type cobweb. Dans les chapitres suivants, ces marchés linéaires sont testés : nous mettons en place plusieurs contextes expérimentaux que nous identifions comme favorisant le déroulement du raisonnement éductif.

Le **chapitre 6** est dédié à la présentation d'expériences sur les marchés de type cobweb où un mécanisme de focalisation des sujets sur leurs prévisions est mis en place. 180 sujets ont participé à des traitements dans lesquels ils devaient prendre deux décisions simultanées, de manière répétée : une décision de production et une anticipation du prix, qui étaient rémunérées selon les règles de calcul du profit et leur qualité respectivement. Les sujets ont été divisés en groupes de petite ou grande taille et les fonctions linéaires ont été transformées en fonctions en escalier ; selon les pentes relatives des fonctions d'offre et de demande, la convergence vers l'équilibre se produit ou pas, et est plus ou moins rapide. Nos résultats montrent que *: i)* avec le temps, les participants deviennent de plus en plus coordonnés et forment des anticipations de qualité ; *ii)* le raisonnement éductif pourrait expliquer le comportement dans les traitements convergents ; *iii)* les prix sont stationnaires ; *iv)* des règles d'anticipation simple ne peuvent pas être déduites de la structure des prix ; *v)* les participants sous-produisent ; *vi)* les décisions de production et les anticipations de prix ne sont pas reliées par une relation de meilleure réponse.

Dans le **chapitre 7**, nous nous penchons plus particulièrement sur l'hypothèse que l'élicitation des croyances améliore la convergence vers l'équilibre ; ainsi, 135 sujets ont participé à des expériences dans lesquelles nous comparons des sessions dans lesquelles les croyances sont élicitées avec des sessions dans lesquelles les croyances ne sont pas observables. Nous formulons quatre autres hypothèses : l'apprentissage ; la coordination ; la cohérence ; le raisonnement éductif. Nous concluons que : *i)* les sujets apprennent et se coordonnent dans tous les traitements ; *ii)* mais ils ne sont pas cohérents dans les traitements dans lesquels les croyances sont élicitées ; *iii)* des règles simples de comportement peuvent expliquer les choix dans les traitements sans croyances ; *iv)* l'élicitation n'améliore pas la convergence et les profits.

Afin de réduire les comportements stratégiques et de rétablir la cohérence des décisions de production avec les anticipations de prix, nous introduisons dans le **chapitre 8** une relation de circularité dans les marchés de type cobweb : le prix qu'un sujet doit anticiper et auquel il vend sa production est déterminé uniquement par les autres membres du groupe et ceci est valable pour tout sujet. Ainsi, en tant que participants dans un marché, les agents sont dans une situation d'interaction locale asymétrique (puisque $n$-1 sont faiseurs de prix et un est preneur de prix) mais en tant que participants dans une économie interconnectée, ils sont parfaitement symétriques car chacun a un double rôle (preneur de prix dans un marché et faiseur de prix dans les autres). La circularité peut s'avérer vicieuse, car si un seul agent adopte un comportement risqué, il entraîne tous les marchés dans lesquels il participe dans un même sens. Pourtant nous faisons l'hypothèse que la circularité pourrait éliminer les comportements non-cohérents et transformer les producteurs en des véritables preneurs de prix. Nous testons expérimentalement ces marchés avec 48 sujets. Nous confirmons notre hypothèse en montrant que : *i)* les prix sont stationnaires autour de l'EAR ; *ii)* même dans les premières périodes de l'expérience, les agents n'ont pas de comportement stratégique ; *iii)* les participants font de prévisions de très bonne qualité ; *iv)* les séries des prix sur différents marchés sont corrélées ; *v)* avec le temps, les participants prennent en compte les prix et leur production individuelle lorsqu'ils forment leurs prévisions, ce qui témoigne de leur capacité de sophistication et compréhension des interactions de l'économie.

# General Introduction

*"Professional investment may be likened to those newspaper competitions in which the competitors have to pick out the six prettiest faces from a hundred photographs, the prize being awarded to the competitor whose choice most nearly corresponds to the average preferences of the competitors as a whole; so that each competitor has to pick, not those faces which he himself finds prettiest, but those which he thinks likeliest to catch the fancy of the other competitors, all of whom are looking at the problem from the same point of view. It is not a case of choosing those which, to the best of one's judgment, are really the prettiest, nor even those which the average opinion genuinely thinks the prettiest. We have reached the third degree where we devote our intelligence to anticipating what the average opinion expects the average opinion to be. And there are some, I believe, who practice the fourth, fifth and higher degrees."*

*(Keynes, 1936)*

In the absence of an auctioneer, the installation of an equilibrium price on a competitive market remains partly an enigma. In order to solve such a problem, Economics research had traditionally chosen the option to populate its models with *homo(s) oeconomicus*. Endowed with unlimited rationality, homo oeconomicus was a standardized economic agent, able to perfectly understand his environment (on which moreover generally had perfect and complete information) and to instantaneously and automatically decide the actions that he had to take in complex situations. However, with the rediscovery of the interest for introducing psychological elements in Economics (among other contemporary contributions), the economic actors became multiple again and the agents recovered their *sapiens* characteristic. When, in 1936, Keynes compared the activities of the financial markets to a beauty contest, he stated in his metaphor this multiplicity of the agents, resulting especially from their various cognitive or reasoning abilities. Imagine a situation where the fundamental equations are publicly revealed, so that all the participants have complete, perfect and symmetrical information about their environment. Even within this *toutes choses égales par ailleurs* setting, the agents are not symmetrical, because they have different cognitive abilities. Thus, each agent processes the data that he receives in a different way, according to his ability of reasoning. The existence of this multitude of agents implies a behavioural uncertainty that the individuals face when they make their decisions. In the absence of certainty on their opponents actions, the agents must form beliefs on the others' strategies before making decisions. The establishment of an equilibrium price results thereafter from a coordination in different agents' beliefs.

A great part of Economics research is devoted to the question of how the agents use the available information to form their beliefs, to provide forecasts and to make decisions based on this activity. The first attempts to explain the formation of beliefs were based on simple rules such as naive or adaptive expectations; since then, empirical evidences put into light the fact that, firstly, the differences of the agents should have a counterpart in the multiplicity of the forecasting rules, and, secondly, more complex forecasting rules of reasoning should be considered, since, as underlined by Keynes, certain agents make use of *winning* strategies. This point marks a return to the concept of rationality, but as resulting from a *process* of reasoning which can be complex. Muth (1961), for example, made the assumption that agents use all available information to set up rational expectations which lead them to the equilibrium through a reasoning *process*, different from the quasi-automatic answers of homo oeconomicus. This new rule requires that the agents have a common knowledge on the environment and use it without making systematic errors and having incentives or benefit to deviate; thus, the agents make good forecasts because it is in their own interest. Guesnerie (1992) suggests a dual interpretation of this assumption: it is right to suppose that it is in the interest of the agents to make correct forecasts; it is wrong to suppose that perfect coordination is the necessary result of the aggregation of isolated optimization efforts. A good forecast must take into account the possibility of bad forecasts from the other agents. Consequently, we should interpret the rational expectations hypothesis as a consequence of rationality and common knowledge of rationality.

Is the rationality of different agents likely to be declined into different *rationalities?* An approach through different degrees of rationality or different depths of reasoning experiences the difficulty of the conceptualization and the transformation into common knowledge of this distribution of different rationalities among agents. Different reasoning abilities are associated in particular with their (cognitive) costs of data processing; each agent thus carries out an advantages-costs arbitration of the reasoning, and determines the limits of the reasoning process put into practice; these limits must be taken into account in the conditions assumed in rational expectations hypothesis.

Our thesis concentrates on the manner in which the agents understand, process and assimilate the data available according to their reasoning abilities. On the basis of this reasoning, we are particularly interested in the way they form articulated beliefs. We evaluate these beliefs because they reveal the cognitive profiles of the agents. Thus, we are interested in the study of the process leading the agents to choose winning strategies and to eliminate the strategies which would not enable them to maximize their benefit (dominated strategies). As the agents are likely to undertake this type of action simultaneously, the available strategies are continuously updated, each agent deploying its reasoning abilities in parallel, while assuming a distribution of profiles for its opponents. It is thus probable that the processes of dominated strategies elimination are put into practice repeatedly, because each agent must take into account the new structure of the environment and other people's beliefs (within the limit of one's cognitive ability) before forming a forecast: thus the reasoning process must be seen as an iterative process.

Information processing, beliefs formation and finally the decision-making, imply the exploitation of one's cognitive abilities, which is a mental complex activity, based on crossed logical operators (forecasting the forecast of the others), called, since Binmore (1987), *eduction*. What is the mechanism of this type of reasoning? **It is exactly this type of question that we will submit to testing in our thesis**. Based on logical inferences, the eductive reasoning proceeds in steps and its success in a population of agents depends on a collective introspection. The rational expectations equilibrium corresponds to the result of an infinite number of steps of sophistication, within a collective infinite eductive reasoning. The more probable assumption would be to consider only a finite number of steps. Each additional step increases the sophistication of the reasoning and determines the depth of reasoning of an agent, which defines its type. Thus the type of an agent corresponds to the last step of eductive reasoning that the agent performs before making a decision. The stopping rule of the sophistication process is determined in an involuntary or voluntary way. In the first case, the last step of the eductive reasoning process of reasoning corresponds to the cognitive ability of the agent; in the other case, the last step of sophistication corresponds to the moment when the agent is able to transform his reflective beliefs (corresponding to the sophistication process) into intuitive beliefs (corresponding to non-justifiable beliefs, not-resulting from any computation): from this moment on, the agent is able to "jump" directly to the equilibrium (if he anticipates that his opponents have equivalent eductive abilities ), or is the winner of the situation (if he perceives his opponents as endowed with lower sophistication abilities).

As this type of reasoning is difficult to put into practice, are there any factors likely to support it? In particular, the eductive reasoning could better perform in stabilizing situations. Any process is characterized by a theoretical evolution path and by oscillations which can make it deviate. In a stabilizing situation, a process is subject to forces that revert it to its evolution path and moderate the deviations. Signals of contrary direction help to better determine the equilibrium and an eductive reasoning process is favoured. The effect of stabilization is due to the fact that any deviation in a direction will be partially compensated by a deviation in the other direction. Substitutable forces must intervene in the environment in order to make it possible. Such an environment corresponds for example to the situation of the agricultural markets: if all the agents anticipate an increase in prices and raise their productions, the market price will go down under the effect of a supply excess. This is a typical negative feedback situation. Thus our thesis is focused on the assessment of the eductive reasoning in this particular environment: **we measure the eductive abilities of the agents in negative feedback situations.**

Experimental Economics offers a favourable framework for the test of this type of reasoning and for the construction of a controlled, not-disturbed, negative feedback environment. Although taking place in people's minds, the eductive process can be revealed through experiments. We experimentally test the mechanism of the eductive reasoning in two types of negative feedback situations: **we introduce a new variant of the beauty contest game (with negative feedback)** and we test a cobweb market. The beauty contest game with negative feedback is in fact the skeleton of the cobweb market.

Since the work of Nagel (1995), experiments on beauty contest games have became popular in Economics, allowing the study of various models of reasoning. The success of these experiments is based on the fact that they can dissociate an eductive mental activity from an evolutive logic. Evolutive arguments, offered by the repetition of the situation, are inherent to experiments where subjects are invited to repeatedly take similar decisions. Even if the conditions of the instantaneous success of the eductive reasoning and asymptotic evolutive convergence are identical (the two processes have the same maps of steps), the eductive reasoning can be identified in the classification of the initial choices. Introducing negative feedback enables us to establish the link with psychological research, by allowing the equilibrium of the game to be interior and by modifying the convergence mechanism of the reasoning process. This increases the chances to reach the equilibrium in comparison to the standard game because the equilibrium is repeatedly scanned and better identified when more eductive steps are put into practice.

Negative feedback market situations are formalized through the cobweb model. The cobweb model is part of the family of models that assume a lag between the moment when the production decision is taken and the moment when the production is actually sold on the market. This model formalizes markets of non-storable goods. Because of this time interval, the agents must form beliefs on the strategies of the others before making their decisions. These models take into account economic environments such as agriculture, where the provisioning must be decided several months in advance. This lag forces the suppliers (the producers) to forecast the price for the following period before the real price is actually known. Thus, before deciding which quantity will be provided on the market, the producers must form anticipations on the future price and base their production decisions on these forecasts: since it takes one period of time to produce the good, the production decision will depend on their anticipation of the price to be established on the market. Thus, the market is mainly driven by the price forecasts and by the resulting production decisions, rather than by the demand side of the request. Expectations about an increase in prices will be followed by a higher production and an excess supply, which leads to lower prices, which characterizes a negative feedback. By testing this market, we investigate the eductive reasoning contingent with several market configurations.

To state it simply, the investigation of the eductive reasoning being put into practice is the main objective of our thesis. We construct this thesis around three questions: what mechanism is the eductive type of reasoning based on? Are there any situations in which this type of reasoning is more likely to succeed? In this type of situation, is the performance of the eductive reasoning improved under particular conditions? We identify the negative feedback environments as stabilizing situations for the eductive reasoning; repetition, elicitation and circularity as conditions for its success. **Our thesis shows that, in negative feedback situations, reflective beliefs turn faster into intuitive beliefs, because through an eductive type of reasoning, the equilibrium is scanned several times, and useful information is increased. This explains why markets with a negative feedback structure are stable and agents within this type of markets hold coordinated beliefs.**

Thus the first chapter constitutes a non-technical introduction into the subject of the eductive reasoning in negative feedback situations. The first part formalizes these concepts in beauty contest games and the second part shows its application in linear cobweb markets. The first chapters of each part (chapter 2 and chapter 5) make detailed presentations of the models. Chapter 2 presents the negative feedback beauty contest games that we introduce and Chapter 5 presents the cobweb model. We also integrate in these chapters the reviews of the former experimental literature relating to our work. However, the main theoretical elements are also included in the other chapters, thus the chapters 3, 4, 6, 7 and 8, in which our experimental work is presented, can be independently read (chapters 1, 2 and 5 providing the technical or argumentative details).

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The thesis is composed of eight chapters. In **chapter 1** we show how is put into practice the process of beliefs formation that agents must undertake in order to answer the behavioural uncertainties they face. This process depends on the characteristics of the situation; within limit-situations agents'expectations can either be based on a focal point, or on a process of complex reasoning in which they "forecast the forecasts of the others"(Binmore, 1987), i.e. the eductive reasoning; intermediary situations are possible. Thus, this chapter introduces the eductive reasoning; that is to remain our interest for the rest of this thesis. As this type of reasoning results from the accumulation of different successive steps, it is probable that the process are not to be carried out ad infinitum, either involuntarily, because the agents have limited eductives abilities, or voluntarily, because they impose themselves a limit, estimating that their opponents will have lower limits. The chapter recalls in a first part the mechanism of the rational expectations hypothesis; the definition of the concept of eductive reasoning with its steps (each additional step corresponds to a degree of reasoning and determines a type of agent); the distinction between eductive and evolutive reasoning; relationships to common knowledge; the role of the cost-benefit analysis in the information processing. In a second part the negative feedback systems are being described: they correspond to situations where every successive actions have opposite consequences; they are strategic substitutabilities situations, where the eductive reasoning is supported and stabilized. We introduce there a discussion of the time that determines the stopping rule of the eductive reasoning, corresponding to the moment when the reflective beliefs become intuitive (Sperber, 1997). We show that this moment rises from the architecture of the verbal communication and is thus "natural" in negative feedback situations; moreover, it is the consequence of the way one makes use of the numbers (Dehaene, 1993).

The thesis is divided into two parts that formalize the introductory discussions of the first chapter. The **first part** makes state of an approach of the concept of eductive reasoning in negative feedback situation by the means of beauty contest games: we propose a new variant of these games that we present then test experimentally. **Chapter 2** thus introduces the negative feedback beauty contest games. In these games, participants have to choose a number between 0 and 100 and the winner is the person whose choice is closest to 100 - *p*mean of all the numbers selected within a group. We mathematically characterize these games: we show in particular that they are isomorphous with traditional beauty contest games, but have an interior equilibrium which is reached by a process of oscillatory convergence with decreasing amplitude, which implies a better localization of the equilibrium because of a better exploitation of the choice interval. Moreover, these games avoid anchoring phenomena and stabilize the beliefs. The chapter also reviews the literature on the traditional beauty contests, in order to present the various modifications and analyses brought to these games, and shows equivalence between these games and the cobweb markets.

In **chapter 3**, we run a one-shot experiment with 324 subjects divided into groups, with parameter p = ⅔, in order to try to establish a typology of the participants according to their depth of reasoning. Our results show that: *i)* the choices are concentrated around the values corresponding to the various steps of eductive reasoning; *ii)* within a model of cognitive hierarchy, the participants correspond to players of type 2 (who estimate that they interact with players who either choose randomly, and/or estimate that the others choose randomly and answer this estimation); *iii)* the speed of the empirical convergence of the reasoning process is faster than in the positive feedback games; *iv)* the simulated repetition of the game starting from the initial configuration would lead faster to the equilibrium than in the traditional game.

In order to verify the result of our simulations and to take into account the effects of repetition on initial choices, in **chapter 4**, negative feedback beauty contest games with several rounds are tested. The chapter starts with a theoretical part in which we formalize the information processing by taking into account the Shannon's entropy approach and the work of Dehaene (1993) on the numbers perception (the SNARC effect). We show that useful information is higher in our games and that there is a point that determines the transformation of the reflective beliefs into intuitive beliefs, depending on the parameter of convergence of the game, *p*: the smaller *p*, the less one needs additional reasoning steps to reach the equilibrium. We test two values of *p*, ¼ and ⅔, with 128 subjects. Our results show that: *i)* the answers can be attributed to players of the type 2; *ii)* the choices are concentrated around the equilibrium; *iii)* three steps of reasoning would be enough to reach the point where the reflective beliefs are transformed into intuitive beliefs.

The **second part** of the thesis corresponds to an approach of the eductive reasoning in simple situations of cobweb markets. These real situations are a direct implementation of the negative feedback beauty contest games. Thus, **chapter 5** presents the linear cobweb model; this model describes production situations of agricultural goods where the production decisions must be made one period before the production is actually sold on the market, and where the producers form forecasts. The conditions of expectations convergence are presented, as well as the equivalence to the preceding games. We also present the mechanism of the eductive reasoning in these markets and various models of limited rationality applied to this type of markets, as well as the experimental literature developed on these topics. In the following chapters, these linear markets are tested: we set up several experimental contexts that we identify like supporting the eductive reasoning.

**Chapter 6** is dedicated to the presentation of experiments on the cobweb markets in which a mechanism of focusing of the subjects on their forecasts is installed. 180 subjects took part in treatments where they had to make two simultaneous decisions, in a repeated way: a production decision and a price forecast, which were remunerated respectively according to the rules of profit calculation or to their quality. The subjects were divided into small or large sized groups and the linear functions were transformed into step functions; according to the relative slopes of the supply and demand functions, convergence towards the equilibrium occurs or not, and is more or less fast. Our results show that: *i)* with time, the participants become increasingly coordinated and form high quality forecasts; *ii)* the eductive reasoning could explain behaviour in the convergent treatments; *iii)* the prices are stationary; *iv)* simple forecasting rules cannot be deduced from the price pattern; *v)* the participants under-produce; *vi)* the production decisions and the price forecasts are not connected by a best-response relation.

In **chapter 7**, we particularly address the assumption that the elicitation of the beliefs improves convergence towards the equilibrium; thus, 135 subjects took part in experiments where we compare elicited beliefs sessions to non-observable beliefs sessions. We formulate four other assumptions: learning; coordination; coherence; eductive reasoning. We conclude that: *i)* the subjects learn and coordinate in all the treatments; *ii)* but they are not coherent in the treatments with elicited beliefs; *iii)* simple rules of behaviour can explain the choices in the treatments without beliefs elicitation; *iv)* the elicitation does not improve convergence and profits.

In order to reduce the strategic behaviours and to restore the coherence of the production decisions and price forecasts, we introduce into **chapter 8** a circularity operator in the cobweb markets. A subject needs to forecast a price determined by the other members of the group; this is valid for any subject. Thus, within a market, agents are in a situation of local asymmetrical interaction (since $n$-1 are price-makers and only one is a price-taker) but within a global inter-connected economy, they are perfectly symmetrical because each one has a double role (price-taker in a market and price-maker in the other markets). Circularity can be vicious, because if only one agent adopts a risky behaviour, all markets in which he is involved are driven in the same direction. However, we make the assumption that circularity could eliminate the non-coherent behaviours and transform the producers into real price-takers (it becomes virtuous). We experimentally test these markets with 48 subjects. We confirm our assumption by showing that: *i)* prices are stationary around the rational expectations equilibrium; *ii)* even during the first part of the experiment, the agents do not have a strategic behaviour; *iii)* the participants make forecasts of very good quality; *iv)* prices series on various markets are correlated; *v)* with time, the participants take into account the prices *and* their individual production when they form their forecasts, which testifies of their ability of sophistication and comprehension of the interactions of the economy.

**Contents**

# Chapter 1

# Assessing eductive reasoning in negative feedback environments: an introduction

## 1.1. Introduction

Imagine a situation in which all agents hold the same information about the environment they face at time *t*. Despite this symmetry of information, agents are not identical because of their different cognitive abilities. Each agent receives and processes information, given his computational ability and, on the basis of this processing, he forms expectations about the state of the world in period *t*+1 or in subsequent periods. An important part of Economics research addresses the question of the use of the available information to form beliefs, deliver predictions and take decisions based on this activity. First attempts to explain expectations formation attached importance to simple rules as (like) naïve or adaptive expectations[1]. However, two empirical evidences put into light the fact that, first, several forecasting rules should be taken into account[2] and, second, more complex rules should be considered. Muth (1961), for example, was motivated by the observation that in simple forecasting rules

[1] Agents with naïve expectations expect today's price to hold tomorrow ($E_{t-1}x_t=x_{t-1}$); agents holding adaptive rules expect tomorrow's price to be a weighted average of the last observed price $x_{t-1}$and the last expected price$E_{t-2}x_{t-1}$.

[2] Different cognitive constraints result in different forecasting rules.

models, systematic errors made by agents are not used to improve future behaviour such that agents keep making the same mistakes without learning. He thus proposed to introduce the rational expectations (RE) rule as a more complete expectations rule. This rule has the advantage that when adopting it, agents do not have incentives to change, whereas under alternative assumptions an individual agent could obtain higher utility by adopting a different rule. This new rule requires common knowledge about the market equations (common understanding of all available information): the complete information set is used by the agents to compute their forecasts. Under the RE assumption, the agents are supposed not to make systematic errors and to have on average the same predictions as the theory[3]. The rational-expectations hypothesis (REH) is thus the extension of the rationality hypothesis to expectations. In other words, people make the right forecasts because it is in their own interest. Guesnerie (1992) suggests interpreting this assertion dually: it is right to assume that it is in the interest of agents to make correct forecasts; it is wrong to assume that perfect coordination is the necessary outcome of an independent optimizing effort of isolated agents. A right forecast must take into account the possibility of wrong forecasts from the other agents. Therefore we should interpret the rational-expectations hypothesis as a *consequence* of rationality and common knowledge of rationality. Recently the Economics research has come to address the question of the amount of knowledge that is assumed for agents to use the RE rules. As the agents have different cognitive abilities, associated in addition with information processing costs, it is possible that their computational resources are limited and therefore a hiatus must be put on the perfect common knowledge assumed in the REH.

Our thesis focuses on the way that the agents understand the available information and assimilate it through reasoning when forming their forecasts in some particular environments that we will describe later. We are interested in the formation and the articulation of economic beliefs. We focus our attention on beliefs that are formed in these environments and that are rationalizable in the terminology of Bernheim (1984) and Pearce (1984). Rationalizable solutions[4] derive from two fundamental principles: individual Bayesian rationality and common knowledge of this rationality. A specific connection is assumed to hold between decisions and expectations: for example today's decisions will tomorrow affect the price on which they are based. We need beliefs to be defined within this framework because we are

[3] "Expectations of firms tend to be distributed, for the same information set, around the prediction of the theory"(Muth, 1961).

[4] Following Bernheim (1984), Pearce (1984) and Guesnerie (1992), rationalizable solutions are conceptually closely related to the successive elimination of dominated strategies.

interested in evaluating them with respect to the cognitive profiles of agents. To put it more clearly, we aim at investigating the reasoning process driving agents to eliminate strategies which would not allow them to maximize their profits (dominated strategies). As in our following studies agents are likely to undertake this type of actions simultaneously, available strategies are continually updated, each agent deploying his respective computational ability in parallel. The processes of elimination of dominated strategies are therefore likely to run several times, because each agent has to take into account the new environment structure (to the extent of his cognitive limits) before forming a forecast: the reasoning process is iterative. Iterative dominance was introduced in Luce and Raiffa (1957) and studied by Moulin (1979), before Bernheim (1984) and Pearce (1984) developed the idea, making the rationalizability popular among economists. Common knowledge was introduced by Lewis (1969) and discussed by Aumann (1976), and formalized by Tan and Werlang (1988). Information processing, beliefs formation and finally decision taking imply the exploitation of one's cognitive capacities, i.e. a complex mental activity based on logic operators that is called, since Binomore (1987), *eduction*. This is the type of reasoning that our thesis will experimentally address in the following chapters.

This type of complex reasoning is difficult to put into practice and therefore we will look for some factors likely to favour it or, at least that do no disturb it; in particular, eductive reasoning could perform better in non-disturbing or stabilizating situations. Our thesis is therefore focused on the performance of this type of eductive reasoning contingent on a precise structure of the environment in which operate some stabilizing factors. We thus examine eductive abilities of the agents in negative feedback situations; we will experimentally test the relevance of these elements in the following chapters.

This chapter is dedicated to the assessment of the eductive type of reasoning in negative feedback situations. Section 1.2 gives an overview of the process of expectations formation. Section 1.3 clarifies the mechanism of an eductive-type of reasoning. In section 1.4 a negative feedback environment is characterized and in section 1.5 some conclusions are drawn. Throughout this chapter, we give a non (or minimalist) technical view of the relevant research on eductive reasoning and negative feedback. We make a way into understanding the *philosophy* of the argument. In the following chapters, relevant concepts will be formally presented.

## 1.2. The process of expectations formation

When people are confronted with a situation, they generally experience uncertainty about the environment itself or about their opponents; therefore, there is a need for agents to form beliefs and expectations. Formally, when the probability of the occurrence of a given event in some situation does not vary with the individual's action, we can say that individuals experience exogenous uncertainty; otherwise, uncertainty is endogenous or behavioural. Keynes (1936)' quotation about the beauty contest is the more famous example in which an individual is put into a situation of behavioural uncertainty in which he has to anticipate "what average opinion expects the average opinion to be". In Economics literature, expectations may be viewed as formalized beliefs and sometimes they are considered as the same concept. By expectations we usually understand attitudes, dispositions or psychological states of mind that relate to uncertain events (Katona, 1951). Three elements are usually involved in an expectation: the individual (who expects), the evidence (what the individual knows) and the prediction (the individual's view of what is going to happen) (Georgescu-Roegen, 1958). The process by the means of which the individual is able to transit from the evidence through the prediction depends on the cognitive ability of each agent and of his cost-resources-benefits arbitrage. Prediction can arrive at once (primary expectations) or in steps (higher order expectations).

In conditions where behavioural uncertainty is predominant, when trying to form predictions or expectations, agents are likely to attempt to detect and understand patterns of regularity and to watch for changes, following their "immensely powerful need for regularity" underlined in Popper (1972). When trying to understand the environment (and especially the others) and its rules of functioning, agents are generally assumed to predict their opponents behaviour using a *theory of mind* (Stennek, 2000; Perner, 1988; Gopnik, 1993). Agents are assumed to make expectations because it helps them to reach the equilibrium; in equilibrium, agents are coordinated. There are several reasons for which they may have reached coordination, that we present as two polar and two intermediary cases:

*i)* the equilibrium is a *focal point*; it is *salient* for agents and it works as a natural attractor for agents strategies. In this case, the agent does not need to put into practice a sophisticated reasoning to select the equilibrium. He just picks the attractor as a strategy that "naturally comes into his mind". This salience situation was described by Schelling (1960) and it corresponds to what is called a first order salience.

*ii)* agents posses high reasoning capacities and make cross-use of them in order to reach the equilibrium. They use complex reasoning processes which lead them to the equilibrium. This kind of sophisticated reasoning in which agents *forecast the forecast of others,* and understand the logic of the game, is eductive reasoning. Even though we consider eductive reasoning as a polar case, this kind of reasoning may not be complete. As it works by cross-forecast, it can be formalized in steps or stages, and the number of steps or stages that an agent put into practice may not tend to infinity. When eductive reasoning is complete, the coordination situation is the one emphasized by Muth (1961) within the REH framework. Notwithstanding, even within a limited number of steps case, it still remains a complex case of thinking, and deep understanding of the model, that will be extensively explained in the following section.

*iii)* in the absence of a focal point and without important thinking capacities, agents may try to use some *reasonable* rules to reach the equilibrium. In this case, the equilibrium is not salient but, cognitively speaking, agents are of the same type as previously: they may want to select a focal point because they have limited computational abilities and the existence of a natural (visible) attractor is an easy task which corresponds to their ability. But when the equilibrium does not exhibit the qualities of an (immediate) focal point, agents have to make use of their limited capacities to come with a strategy and thus they provide strategies that are reasonable given their thinking capacity. This case corresponds to models of classic bounded rationality, i.e. naïve, adaptive learning, etc[5].

*iv)* in the system there might be a focal point, although the agents do not use this first-order salience, but best-respond to first-order salience and may do it repeatedly (*n*-order Shelling salience). In the limit, the equilibrium will be a revealed focal point[6]. This process occurs in steps, but not under the same premises as eductive reasoning. Stennek (2000) defines a hierarchy of increasingly *intelligent* decision-making procedures, which reason analogously to the levels of strict dominance. The bases of this hierarchy are non-rational procedures wherethe

[5] In Chapter 5, several models of limited rationality will be explained in the particular case of a cobweb market.

[6] A natural focal point is spontaneously salient; a revealed focal point is reason-salient, i.e. it corresponds to the point of convergence of the *n*-order salience; an eductive focal point is singled out through eductive introspection.

actions are chosen according to their unmodeled salience. Their choices are taken into account in the consecutive higher order procedure, which is rational and chooses an undominated action. Higher order procedures are defined in a similar way until the last infinite-rationality procedure where iterations are to be conducted ad infinitum.

We indicated in this classification that, on the one hand, there are simple processes of expectations formation depending on limited rationality; on the other hand, there are processes of expectation formation occurring in steps but likely not to be driven ad infinitum. There are differences between expectations processes limits:

*i)* characteristic limited rationality is involuntary, i.e. agents use proxies instead of a full understanding of the system.

*ii)* rationality limits are self-imposed when agents are able to jump intermediary reasoning stages and understand the equilibrium.

When an agent ignores the decisions of his opponents at the moment of the decision-making, following Bernheim (1984), rationality consists of making a choice justifiable by an internally consistent system of beliefs, rather that a *post hoc* optimal one. Simon (1982) also considers behaviour as rational when it is the outcome of an appropriate deliberation process. The hypothesis that Nash equilibrium may be directly salient for agents is stronger than the hypothesis that agents attempt to second-guess each other, assuming that their opponents do the same. Bernheim (1984) introduces and justifies a new notion as follows: an agent must construct an assessment on an opponent action and optimize accordingly. This assessment must be consistent with everything the agent knows about the game. Among other things, the agent knows that his opponent has also an assessment in return about what the agent will do, for which the opponent's answer is a best response. In order to preserve consistency, the agent must not only have an assessment of what the opponent will do, subject to which the agent's choice is a best-response, but for every forecast of the opponent strategy, to which the agent assigns positive probability. The agent must also be able to construct a conjecture of the opponent assessment on the agent's action, for which this forecast of the opponent strategy is a best response. This reasoning can be extended ad infinitum. If it is possible to justify the choice of a particular strategy by constructing infinite sequences of self-justifying conjectured assessments in this way, the strategy is *rationalizable* (as defined by Bernheim (1984)). But, in practice, agents may only check the consistency of their beliefs for a finite number of levels.

The type of expectations that drives the system determines the kind of equilibrium attained. Generally speaking, expectations are based on several closely connected mechanisms: observation, repetition and understanding. When all these processes are complete, the REH paradigm emerges and drives the system to the rational expectations equilibrium (REE). A REE can be characterized by three main features: *i)* market clearing at the equilibrium price; *ii)* the relation between price determination and private information is known by every agent; *iii)* agents fully exploit the information contained in prices. Therefore the REE has a dual role: clearing the market and making public private information.

But Arthur (1994) argues that humans are to use perfect rationality until a surprisingly modest level. Therefore, we have to take into account the fact that the REH may be declined and used to several different extents, separated by the degree of (intelligent) computations that are run before decision-making[7]. Therefore the theory of mind is a specific cognitive ability to understand others as reasoning agents, i.e. to interpret their minds in terms of theoretical concepts of intentional states such as beliefs (Davidson, 1980; Gordon, 1986), and to perform mental simulations to the extent of their cognitive *resources*, giving it more economic flavour. The question is not to know if agents possess unlimited rationality, but to know what approximations of rationality could provide outputs as good as unlimited rationality and how close to the limits are we. Therefore, we will analyse the internal process of the rational expectations process, i.e. the steps involved in eductive reasoning.

Two main questions about expectations are relevant to our research: why are expectations important and how can we observe expectations. Expectations will be seen as two-dimensioned: agents form expectations about the economic values and interactions, and this confers them a strategic dimension; as beliefs, expectations have a cognitive dimension.

Therefore, addressing the first question, expectations are important because they link economics to cognition and behaviour. It is in this sense that Keynes stressed the conventional role of expectations in the financial market activity or speculation; Hayek analysed the role of information in markets self-organisation; this question was also addressed by Simon who took

[7] To point the difference with the classic bounded rationality literature, this can be called bounded or limited REH.

into account the economic constraints in obtaining and processing information; Aumann formalized common beliefs pre-coordination role; Muth stressed an optimal utilization of the information when forming anticipations; finally Sperber analysed the arbitrage process between the cognitive effort and beliefs pertinence. Experimental economics addresses the question of how to observe expectations and this leads us to our second question.

In real markets, it is difficult to obtain detailed and unbiased information about agents' expectations. Moreover, we are not able to correctly define the amount of knowledge that agents in real markets hold about the market. Experimental economics offers a tool to generate expectations in laboratory. The fundamentals of the economy and the information that is delivered to subjects are controlled. Experiments allow for the collection of expectation without additional noise and replicating several times the same environment. Since experimental economics has become an important field of Economics research, several experimental studies have analysed beliefs and/or expectations. The literature related to eductive reasoning, games designed to study sophisticated reasoning (beauty contest games) and the role of negative feedback (cobweb markets) will be reviewed in chapters 2 and 5. Chapters 3, 4, 6, 7, and 8 in this thesis are devoted to different experiments designed to collect expectations that we will analyse. Davis and Holt (1993) and Kagel and Roth ( 1995) stress that the main objectives of an experiment are theory falsification, sensitivity tests and the search for empirical regularities. All these objectives will be addressed in our attempt to understand eductive reasoning: we will test it, we will investigate how it is affected by changing fundamentals, and we will look for empirical regularities.

## 1.3. Clarifying eductive reasoning

We follow Binmore (1987) and Guesnerie (1992) to first define the concept (1.3.1), and differentiate this concept from evolutive reasoning (1.3.2). We establish the links with the common knowledge concept (1.3.3) and with information processing (1.3.4)

### 1.3.1. Definition

Following Binmore (1987), the word *eductive*[1] is used to describe a dynamic process by means of which equilibrium is achieved through careful reasoning on the part of the players before and during the play of the game. Eductive reasoning is therefore a part of a rational decision process and describes the entire reasoning activity that intervenes between the receipt of a decision stimulus and the ultimate decision, especially including the manner in which the agent forms the beliefs on which the decision will be based. This is the mental activity involved in *forecasting the forecast of others*. This type of reasoning occurs in *steps*. As steps imply oscillations, Binmore (1987) suggests that notions as equilibration or adjustment process should be better understood under the designation *libration*[2].

The eductive reasoning concerns data processing, i.e. how the agents model their reasoning processes by inputting data in the reasoning processes. Such considerations are internal to a player. The dynamics of an eductive reasoning and other data on the internal thinking process that another co-player may use are not observable. Therefore, as emphasized by Binmore (1987), Guesnerie (1992) and Walliser (2000), such reasoning usually requires an attempt to simulate the reasoning processes of the other players. Eductive reasoning implies careful cross-thinking, symbolized by the lines "if I think that he thinks that I think…". But this premise requires that the information is available on how an opponent thinks. If real data does not exist, performing simulations on other players' minds could be done by introspection, which can be a practical method for predicting the behaviour of others. More specifically, in order to predict what an opponent will do in a situation that cannot be observed, an agent uses what it would do itself, if it were in the same situation, as a guideline. But introspection is not as simple. In the following we will refer to introspection as the process in which an agent incorporates in his own reasoning behavioural elements from other individuals programs, about which he learns to have been successful, and deletes the less successful elements of its original thinking program. In the long run, the tendency will be to generate through imitation and education a population with closely similar thinking programs and hence its members will have good reason to suppose that introspection is a valuable source of information about the thinking process of others.

[1] To educe = to bring, to drow out, develop, extract or evolve from latent of potential existence; infer a number, a principle, from data or from another state in which it previously existed (from the Latin word *educere*, lead) (Oxford English Dictionary)
[2] Libration = very slow oscillation (from the Latin word *libra*, scale) (Oxford English Dictionary)

A player endowed with the capacity to put into practice an eductive-type of reasoning can forecast the forecast of others and simultaneously participate in the same game. Being able to introspect while the decision is taken requires that the internal complexity of agents using eductive reasoning is large compared with that of the environment[10]. For the needs of the simulation, rational players can perfectly duplicate the reasoning process of their opponents and hence perfectly predict their strategies. In an eductive setting, a player needs to be able to state complex hypotheses about the reasoning processes of his opponents. Therefore, to the usual issue of modelling the others as being the same as his own, eductive behaviour must include the possibility of bad play by the opponents and the capacity for an agent to exploit it.

Describing the functioning of the eductive reasoning implies describing and following calculation steps that have to be taken into account when the process is put into practice. The system is driven by a computing apparatus endowed with storage space for all elements it may use in calculating. During the calculation, intermediary results are kept in this working memory. What happens at any step in the calculation depends on the internal state of the agent and of his inputs. These factors determine how the agent will calculate and especially the next internal intermediary step to which the agent moves. Based on the rationalizability concept, eductive reasoning steps can be described as following[11]:

*i)* each agent is rational; he only uses strategies that are best responses to some possible profile of strategies that can be actually played by the others; hence, non best-response strategies are eliminated from the strategy space;

*ii)* each agent knows that all other agents are rational and imagine a hypothetical distribution of agent types, in which he defines a proportion of agents that are able to perform the previous step; thus several non-best responses to this state are eliminated from the initial strategies set;

*iii)* another proportion of players are able to perform the previous step and this is commonly known.

…

*(p)* all agents know that all agents know that all agents know….that agents have performed the previous steps.

It is important to define a stop procedure, i.e. an agent performing eductive reasoning must finish his calculations at some step corresponding to his cognitive limit or to one more step

[10] Simon(1955, 1959, 1977) describes agents for which internal complexity is low.
[11] Adapted from a specific example in Guesnerie (1992).

over what he expects of his opponents. Stopping at some step does not mean eductive reasoning regression is finite, but simply that agents are able to save their efforts by only providing the number of steps that is contingent with the situation and their beliefs about opponents. The stopping rule appears as a rule of thumb for determining when convergence has been sufficiently achieved, i.e. when the estimated (small) cost of moving one more step outweighs the estimated benefits of a more refined prediction.

A rational agent cannot be seen as a unique type. An agent is assumed to recognize *n* different possible types of agents, distinguished by the way they process the objective data that they may have received. The existence of different types of agents performing eductive reasoning implies that several stopping rules exists, therefore the eductive reasoning is likely to be interrupted at different moments. Not pushing an eductive procees until the end can be considered as a deviation from perfect play. This leaves the possibility of explaining deviations from predicted play without the necessity of abandoning the hypothesis that the opponent is rational. Even if the trembling hand provides similar possibilities, in an eductive context these explanations have to be of last resort (Binomore, 1987).

As real life situations always involve some explicit or implicit constraints on the cost of an action, cost of calculation must be taken into account when describing the eductive process and the stop device. A possibility that had been evoked is to hypothesize meta-players who design the players that actually play (Megiddo and Wigderson, 1986; Neyman, 1985; Rubinstein, 1985; Abreu and Rubinstein, 1986): these meta-players are seen as playing a meta-game where a pure strategy is the choice of players. But this approach only transfers the problem. The example given in Binmore (1987) is the examination of the status of an auctioneer in the Arrow-Debreu model of a market. Except under rare circumstances, such an auctioneer does not exist. Calculating prices instead is achieved through an unmodeled tâtonnement process for which the auctioneer serves as a simplifying substitute.

Usually, theoretical realizations of bounded rationality incorporate a fixed, exogenously determined, upper bound on some aspect of the complexity of the strategies available to a player. Bounded rationality in this sense is not costly rationality as far as in an eductive context, a minimal requirement is that the marginal cost of calculation must always be very small. Thus, if a player fails to carry out certain computational tasks in equilibrium, it is because the agent has chosen not to do so, not because it is unable to do so without abandoning other computational tasks. In an eductive context, any computational constraint on an agent must therefore be endogenous (self-imposed). A player must be able to recognize and respond to (expected) deviating behaviour.

### 1.3.2. Distinction eductive/ evolutive reasoning

As a strictly eductive environment is seldom encountered in the real world, evolutive factors always contaminate the analysis of eductive settings. The word *evolutive* describes a dynamic process by means of which equilibrium is achieved through evolutionary mechanisms. Binmore (1987) includes in this type of reasoning very long-run processes studied by evolutionary biologists (Smith, 1982), but also medium-run processes where the population dynamics are not necessarily based on genetic considerations (Friedman and Rosenthal, 1984), as well as very short-run processes by means of which markets achieve clearing prices (Marschak and Selten, 1978; Moulin, 1981). The linking consideration is that adjustment takes place as a result of iterated play by myopic players.
The dynamics of an evolutive process is external and visible to the observer. It sometime occurs in the same sequence of steps as eductive reasoning. Therefore, the distinction between an eductive (mental) and an evolutive (statistical) process is quantitative rather than qualitative. In the former, players are envisaged as having potentially very high complexity (with low operating costs) whereas, in the latter, their internal complexity is low. Few researches have been made so far into this area (Neyman, 1985; Rubinstein, 1985; Abreu and Rubinstein, 1986).

Through both processes, the situation evolves. In an eductive setting, evolution (as seen from the exterior) operates *at one remove*, because notional time cannot be observed; in evolutive processes, evolution works *in real time*. Strategies of one specific game are directly influenced and evolve in evolutive theory. When costly rationality is taken into account, this means that the evolutionary process act directly on the rules of behaviour which implement these strategies. In eductive theory, on the other hand, evolutionary processes work on a meta-program with the capacity to choose strategies in a wide variety of different games, several being never played before.

### 1.3.3. From common knowledge to eductive reasoning

In order to handle interactive situations, agents must have not only individual and independent knowledge of the fundamentals (usually this situation is called first order knowledge), but also *interactive* knowledge (higher order knowledge), i.e. knowledge about others' knowledge. When acting in such situations, agents' behaviour is significantly influenced by their knowledge about the others' knowledge; moreover, by the knowledge they have about others' knowledge about their knowledge, and so on. When such reasoning is applied infinitely and leads to identical knowledge for every agent, this kind of knowledge is called common knowledge(CK). To put it more precisely, a knowledge is common among a group of agents if everyone has it, everyone knows that everyone has it, everyone knows that everyone knows that everyone has it, and so on ad infinitum. Actually, it is simply an infinite regress of reasoning about agents' knowledge unifying the set of distributed knowledge. It makes collective knowledge completely transparent to each individual.

As this notion is constructed in steps, it can be characterized by the numbers of steps accomplished, i.e. the depth of knowledge. Morris and al. (1995) introduce a formal definition of the depth of knowledge that we adapt here to describe agents' insertion in the informational structure of an environment. Confronted to an environment where information about the fundamentals is symmetrically delivered, agents naturally split into types according to the extent of each agent understanding or processing information abilities.

Thus, we transfer the depth of knowledge notion from the environment to the individual and say about an agent that he has a *k*-depth of knowledge if he is able to understand the CK structure of the environment until iteration *k*. Therefore, an agent endowed with depth of knowledge *k* is supposed to have accomplished *k* iterations of knowledge. Attaining one additional *unit* of depth of knowledge requires implementing a step of eductive reasoning. Therefore, an agent holding extended[12] knowledge depth about market equations is supposed to have accomplished *k* steps of eductive reasoning. An agent reaches his *type* by eductive reasoning or introspection on the information he receives.

The truth of the assertion (everybody knows)$^N$ (Guesnerie, 2004) that the agents are rational, whatever *N*, defines common knowledge of rationality. Hence, as defined, common knowledge of rationality (and of the game) implies that all agents have *perfect foresight*: the

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[12] By extended knowledge we understand knowledge about the environment with all its *mathematical* implications, i.e. the extension of knowledge to rationality.

equilibrium is guessed or educed through the process just described; it may be called eductively stable or strongly rational.

### 1.3.4. Information processing costs and eductive reasoning

When describing eductive reasoning, we are only interested in contests. Binmore(1987) uses this term to indicate a game with no pre-play communication between the players. But the impossibility for players to communicate before and during the game does not imply that they do not share information supplied during the game. Among other things, they will share knowledge about conventions involved in the population. Such conventions allow players to coordinate their behaviour by making use of the fact that they can commonly observe phenomena which are not intrinsic to the game, i.e. common understanding. When two rational players face each other in a game, their choices of strategies will be approximately optimal given their predictions of the strategies to be chosen by the other player. However, this prediction need not always be realized because of indeterminacy. Therefore, when computing an answer to a game, an agent must previously identify his opponent as belonging to the same population. Players are satisficers in the sense that they will calculate only to the extent of an appropriate level of approximation.

The assumption of null informational cost is unrealistic. Whenever understanding (by processing) information is costly, a rational agent face the decision problem of whether the expected benefit of acquiring or processing the information is worth the cost of processing it. Therefore the amount of information processed by individuals becomes an element of the decision making process. When full rationality is scarce, the deliberation cost must be taken into account (Conlisk, 1996) because good decisions are costly. There is a trade-off between effort devoted to deliberation and possible outcome, described by Day (1993) as the *economy of the mind*. Establishing a deliberation model was the purpose of research by Marshak and Radner (1972), Selten (1978), Radner and Rothchild (1975), Evans and Ramey (1992,1995). These models generally show how the deliberation technique can merge optimization, rational expectations, and the degree of rationality of a decision is endogenously determined by *economic* calculations. Tirole (2002) describes a simple situation with a three-period horizon ($t$ = 0,1,2). At $t$ = 0, the agent is assumed to have prior information on the situation. At time $t$ = 1, he will decide whether or not to exert some introspection effort at a positive cost. Effort results in a probability of success that can be interpreted as ability in the task. When deciding to exert effort, the agent perceives (immediate) current cost to be compared with discounted expected benefits from effort. Therefore ability and effort are either complements or substitutes in generating outcomes.

### 1.4. Beliefs retroaction into the system: the case of negative feedback

Besides individual cognitive processes that agents put into practice in decision making situations, there is evidence, especially on financial markets, that shows that agents' expectations and representations can also be transformed under the action of the others and of the market itself (collective (Orlean, 2000) or environment-based dynamics). We therefore have to assume that any model of (rational) reasoning will deliver different performances in different environments. In particular, a reasoning process is expected to better perform if no external forces disturb it, or especially in a stabilizing framework. A distinction can be envisaged between confirming environments (where only the direction indicated in the reasoning process is confirmed) and stabilizing environments (where the localization of the equilibrium is educed). Confirming environments are viewed in the literature as positive feedback or strategic complementarities environments and stabilizing environments are represented by negative feedback or strategic substitutabilities environments. As the process under scrutiny here is eductive reasoning, a rather complex process, we will investigate it in negative environments, likely to favour eductive reasoning. Section 1.4.1 will describe such environments; section 1.4.2 will assesses stability criteria in such environments; sections 1.4.3 and 1.4.4 are concerned respectively with intuition and reflection in negative feedback environments and with number attitude.

#### 1.4.1. A simple description of negative feedback

Following Arthur's (1989) work, more and more attention has been devoted in Economics to the idea of positive feedback. The idea underlying positive feedback is that of a change in the world provoking subsequent changes, of similar character but greater magnitude; examples stand in the capitalist idea of growth, expanding markets, innovations and never-ending progress that have interested economists for long. On the contrary, negative feedback describes situations where any two consecutive changes have opposite properties, as in perishable products markets, or financial investment, where any common action results in an opposite result as compared to individual action. For example, if crop producers believe that market prices will be high, a high production for a single individual will imply high earnings from the selling activity for this individual, but generalized high production overfeeds the market and prices, together with individual profits, will collapse.

Using words like *positive* and *negative* does not account for *right* and *wrong*. As we will explain in the following subsection, these names are only the extension of derivation signs within any sequence of consecutive changes: positive feedback deals with similarity and positive first derivative (+), whereas negative feedback deals with opposite effects and negative signed derivative (-). Therefore, positive feedback is not necessarily "positive" and negative feedback is not necessarily "negative". For example, as pointed out by Batten (2004), on a highway, when congestion begins to slow down traffic, a downward spiral that will lead to a traffic jam forms. As it begins operating, it functions under positive feedback loops slowing traffic down and ultimately bringing it to a deep basin of attraction. Every action that slows down traffic - slamming on the brakes, rubbernecking to see an accident - produces more of the same effects. The feedback is positive but its consequence is *negative*: the flow of traffic is decreasing. Let us suppose that traffic is completely paralyzed: we are at a point where there is no more change, so no feedback actions, because nothing happens. Acts that could produce a change (a clearing in the traffic) tend to be dampened, rather than amplified, as everyone rushes to exploit them and thereby nullifies them. The system has moved towards negative feedback even if the purpose of actions is a *positive* one. Batten (2004) describes a model of a dynamic world with several punctuated equilibria defined as attractors or steady states that the system is likely to attain without any particular order. Continuing the previous example, one equilibrium is a state of swiftly flowing traffic, and another is a stop-and-go traffic jam. If the system approaches an attractor, the effect of negative feedback can catch it and keep it there until the process repeats.

We therefore identify a stabilization effect in negative feedback environments and make the assumption that eductive reasoning will perform better in such environments, since its internal coherence is preserved from disturbances and kept in the eductive path. A clarifying point must also be stated about feedback: positive and negative feedbacks should be described as *effects*, rather than forces. In fact, stabilization works more as an equivalence rather than an oriented implication from one process to another: as a system approaches a steady state, there is not an overarching force of positive feedback that must be overcome. Thus, following the same cited example, when traffic slows down to a jam, we need not look around and wonder what happened to the positive feedback that was driving the change. The positive feedback was an effect of the cars slowing down: once the cars have stopped, we're not going to observe this effect anymore. Therefore, self-enforcement of the rule operates in negative feedback environments. As we will explain later, if we expect eductive reasoning to perform better in negative feedback situations, this is because such a process is inherently driven to equilibrium in such a case. In particular, as pointed by Arthur (1990), negative feedback tends to stabilize the economy because any major changes will be offset by the reactions they generate. Parts of the economy that are resource-based such as farming are subject to diminishing returns and therefore to a negative feedback configuration. The cobweb environment described by Muth (1961) offers the simplest picture of a negative feedback setting. Chapter 5 will be dedicated to the detailed presentation of such a cobweb economy. In the current chapter we will explain the mechanism through which negative feedback operates.

### 1.4.2. Stability arguments in negative feedback environments

One of the implications of the REH is that expectations are endogenous: they are contingent on the predictions of the relevant economic theory and are self-fulfilling. But as explained earlier, we are interested here in the moment when the reasoning chain underlined by the REH breaks. When the reasoning process stops, the configuration of the situation can be stable or unstable. In order to understand what exactly happens in a negative feedback environment populated by agents with different cognitive abilities, we have to explore the analytical regularities of economic interactions in such an environment. Through a self-fulfilling process, where do expectations drive the situation within a negative feedback setting? Previous assumptions state that the system is driven to stability (to equilibrium). We aim at explaining why and how.

Let us describe a negative feedback environment, following Guesnerie (2004). There is a continuum of agents, each of them concerned with his own action and with aggregate data, on which a single agent only has infinitesimal influence. Each individual $i$'s best response depends on the subjective probability distribution of the aggregate data, denoted $p(i)$. To a profile of individual distributions, $P = (\ldots p(i) \ldots)$, an aggregate situation $B(P)$ is associated, where operator $B$ denotes agent $i$'s best response to the aggregate situation, $B(i, p(i))$. In equilibrium the argument and the realization of the operator $B$ coincide. Let $A$ and $A'$ denote two collections of such point expectations. Negative feedback means that each individual best response function is decreasing in its argument, i.e., given $B(i, A') > B(i, A)$, $A' < A$: to each state of the world, the best-response function gives an opposite new state of the world. Such a formalization has been analysed by Topkis (1979) and Guesnerie (2004) for positive feedback situations, called strategic complementarities situations. By opposition, negative feedback situations are assimilated to strategic substitutabilities situations. As in game theoretical and experimental literature (Van de Velden, 2001; Guesnerie, 2004), both formulations are used to describe situations where best-response functions are decreasing, we will use in the remaining of this thesis several times the denomination "strategic substitutabilities", but we will rather prefer "negative feedback".

Let us consider a one-dimensional vector denoted $a > 0$. Strategic substitutabilities or negative feedback assume $( dB /da ) < 0$, as in the Muth's (1961) model. As agents involved in the model are producers, the variable $a$ denotes the size of the crop. As price of the crop decreases with $a$, the size of the supplied crop, $B(a)$, associated with expectations $a$, decreases with $a$. The unique equilibrium can be educed as we will explain later, in steps. Guesnerie (2004) gives the following explanation: if some farmers with high costs do not join, then the crop has a maximal size implying a low price, but no so low to prevent a few efficient enough farmers to be willing to produce. But, with the aggregate crop produced only by low cost farmers, the price will be lower than some high threshold, so that some farmers, who a priori wanted to join, drop, so that the price will be higher than previously assumed, so that more low cost farmers will join etc. The process is more formally described in Guesnerie (1992) and in Chapter 5. The unique equilibrium is globally eductively stable if $B$ has no cycle; it is locally eductively stable *if* the ratio of the price elasticity of aggregate supply over the price elasticity of aggregate demand is smaller than 1.

Thus $B(a)$ describes the aggregate state of the system[13] as a function of point expectations $a$. Starting from an initial reference point (that can be one of the borders of the definition interval of $a$, for example the inferior bound 0), the eductive argument adapted to such an environment is the following:

*i)* *Step* 0: given the negative feedback structure of the environment, $B(0) > a$.

[13] As $a$ is a collection, we can write $B(a)=a$.

*ii)* *Step*1: everybody knowing *i)*, given the negative feedback, the final state of the system $a$ will be such that $a > B \circ B(0)$.

*iii)* *Step* 2: everybody taking into account the outcome of the previous step (they know and know that the others know), the situation will be such that $a < B \circ B \circ B(0)$…

The process continues with any step $k$ taking into account the conclusion of step $k$-1, and with $a$ alternating positions around compositions of function $B$. Therefore, if $a$ belongs to a closed interval, there is an unique equilibrium, which is a focal point singled out by the eductive mental process, whereas in the polar case of strategic complementarities or positive feedback, uniqueness of the equilibrium is not guaranteed.

### 1.4.3. Intuitive versus reflective beliefs in negative feedback environments

According to the Economic Psychology literature (Franz, 2003), human thinking (or reasoning) continually performs three operations: scanning data for patterns, storing them in memory, and applying them to make inferences and take decisions. There are situations where the last operation is reached only through careful, elaborate reasoning; but in some other situations, people are able to spontaneously take decisions. In this paragraph we will briefly remind the functioning of reasoning, as stressed in Sperber (1997)[14], Simon (1965-1997) and Frantz (2003), and that we adapt to the context of negative feedback environments.

We focus here on the study of beliefs as structuring elements of reasoning. Human mind possesses two kinds of beliefs, intuitive and reflective beliefs. No reflection or specification of particular justifications are needed in order to hold *intuitive* beliefs. But when we are able (need) to draw inferences, to *process* representations (or information) following a scheme or several stages (by using knowledge, common knowledge and reasoning), we hold *reflective* beliefs. When interacting with their environment, agents are usually able to hold these two kinds of beliefs simultaneously, because the human mind has the ability to hold simultaneously representations as (intuitive) beliefs and as a meta-representational ability (of reflective beliefs). Simon and Gilmartin (1973) stress that intuition is not a process that operates independently of analysis, but by effective decision-making. Reflective beliefs need a validating context or a validating mechanism, whereas intuitive beliefs need what Sperber

[14] This is not at the origin an economic argument, but we consider it as very useful in understanding our research question of eductive abilities, as it incorporates discussion in terms of costs and benefits.

(1997) calls a creedal context, in the sense that no proof is required when an intuitive belief is activated[15]. Bunge (1962) refers to rapid reasoning and Simon (1973) refers to it as subconscious pattern recognition. If an agent holds the intuitive belief *P*, and if *Q* is inferred *spontaneously* from *P*, it is reasonable to attribute to the agent the intuitive belief *Q*. No hierarchy exists between intuitive and reflective beliefs, because intuitive beliefs can turn into reflective beliefs and vice-versa. Simon (1997), for example, defines intuition as analytical complex reasoning (i.e. based on reflective beliefs) frozen into habit and into the capacity for rapid response through recognition of familiar kind of situations, thus as transformed reflective beliefs. But what exists, is an internal architecture of the human mind storing all types of beliefs.

Talking about storing, and previous considerations on bounded rationality, imply that we consider the representational capacity of an agent is limited. Intuitive beliefs are likely to require less space than reflective beliefs (where intermediary statements are equally stored). Sperber (1997) argues that in a language, one may need a concept unavailable in its mental lexicon; one will thus meta-represent this concept with the help of available intuitive concepts: this is the general acceptation of the transition from intuitive to reflective beliefs. As operation repeats, the new meta(constructed) concept may become immediately available: this way a reflective concept turns back into an intuitive one. Paraphrasing Poincaré, "inspiration comes only to the prepared mind". Remind that the first purpose of our research is to find when exactly and why is an eductive reasoning likely to stop. We put forward two assumptions about this precise moment:

*i)* an agent is likely to stop the eductive reasoning at step *k* if his storing space becomes full at this moment and no space is left for additional introspection steps; the stopping rule is therefore implied by the cognitive (storing and working) capacity of the agent: he stops at step *k* because he fulfils at this step his cognitive constraint (agent has eductive ability *k* or is of *k*-type);

*ii)* an agent is likely to stop the eductive reasoning at the moment when it becames possible for him to transform the last of the consecutive (reflective) eductive steps into an intuitive statement: an agent stops calculating when it is possible for him to *jump* directly to the (intuitive) equilibrium; in this case, agent's eductive ability is

[15] "All beliefs that are output of perceptual processes are intuitive in a standard psychological sense, and so are all beliefs that are the output of spontaneous or unconscious inferential processes taking intuitive beliefs as premises […]. When any type of beliefs serves as a premise in a deliberate derivation of further beliefs, the inferential process in which they are involved [leads to] non-intuitive or reflective beliefs". (Sperber, 1997).

higher than the index *k* of the step at which he stops: the agent stops because it becames easy for him to reach the equilibrium point and therefore by doing that he saves efforts and minimizes calculation costs.

What we will demonstrate all along the following chapters is that in a negative feedback environment agents beliefs are more likely to be driven by the second assumption. How easily may reflective concepts become intuitive? How does a negative feedback environment favour such a process? In Sperber (1997), two possible answers and a factual example are suggested. According to a radically empiricist view, no concept is immediately intuitive, but all concepts may become intuitive, provided they are used often enough; according to a radically nativist theory (that the author is closer to), there is an innate range of intuitive concepts, a subset of them being actualized in the intuitive repertoire of any given agent. The example lies between these two views: the example is used to identify the moment when reflective beliefs become intuitive. We adapt the example as follows: imagine agent *i* is holding a visibly "lemon" car; agent *j* observes it and makes statement "what a beautiful car" about it. Agent *i* knows that his car is a clue; agent *j* knows it too; agent *i* knows that agent *j* knows; agent *j* knows that agent *i* knows that agent *j* knows… These iterations are enough for both agents to fully understand the previous agent *j*'s statement. So far, at least 3 iterations have been rapidly made without any particular effort. We are able to communicate at level 3 in day-to-day life within a negative feedback situation and communication works well. This does not hold within a positive feedback situation (if the car *is* beautiful). We therefore conclude that reflection turns into intuition in the neighbourhood of the natural degree of communication (and mutual understanding) in negative feedback environments. We thus expect to find experimental proof of such convergence.

### 1.4.4. "Numbers attitude"

As stressed before, we intend to address the eductive reasoning question in contests, i.e. in game with no pre-play communication. We insert our research in experiments based on the muthian model designed by Guesnerie (1992) and on beauty contest games adapted to negative feedback. In all these experiments, agents are likely to deal with numbers (they may guess numbers, forecast prices or take decisions on quantities). In this paragraph we therefore refer to a study run in experimental psychology by Dehaene and al.(1993), where the authors explain how people perceive and make use of numbers. The article is concerned with numerical abilities of agents and several regularities are observed in experiments. Among other results, we are interested here in the SNARC (Spatial Numerical Association of Response Codes) concept: numbers are perceived on a scale on which large numbers are associated with one side and small numbers with the other side. The particular direction of the special-numerical association is determined by the direction of writing: small numbers are situated at the left side and high numbers at the right side[16]. What is essential in this numbers architecture is the order: when switching from a number $x$ to another number $y$ the order must be respected, i.e. all numbers between $x$ and $y$ are bypassed and inversely. Let us imagine an agent who plays a contest with a negative feedback numbers system. At each choice, the system brings the agent in an opposite direction. Let us suppose that the eductive reasoning steps (that the agent is supposed to consider when making choices) are made in real time rather than in notional time and are thus observable. Suppose that at the first iteration the agent switches from $x$ to $y$, with $x < y$; at the second iteration the agent switches back in the direction of $x$, to $z$, with $x < z < y$ and then back to $t$ in the direction of $y$, with $x < z < t < y$ and so on[17], and the process converges to an equilibrium that is likely to be situated between $z$ and $t$. Therefore, at every switch, the equilibrium number is bypassed; the agents "sees" the equilibrium several times. On the contrary, in a positive feedback situation, equilibrium is outside the sequence of intermediary steps and more and more iterations do not help the agent to find it. This is the intuition of the argument. We will formally explain in Chapter 4 how this evidence about number architecture benefits to the agent in a negative feedback situation and helps him to find the equilibrium.

## 1.5. Conclusion

The aim of this chapter was to introduce the notion of eductive reasoning and to show why it is important to analyse it in a context of negative feedback. The chapter thus introduced notions and ideas that will serve as a basis for the experimental work from chapters 3, 4 and 6 to 8.

Imagine a situation of social or economic interaction with individual agents needing to take simultaneous decisions; all fundamentals are known. In such a context, people face

[16] For Europeans, for example.
[17] We describe here a convergent process.

behavioural uncertainty about their opponents, as they do not hold in their informational set concrete elements about the beliefs that will lead their opponents to take a decision. We can expect people involved together in an economic situation to be willing to reach the equilibrium in that particular situation. Interactive situations are in equilibrium when all agents that participate to the situation are coordinated. In particular, in equilibrium, agents coordinate their understandings of the situation, and they are compatible: thus coordination passes through beliefs.

Coordination can either be immediate or reached by some process. When coordination is immediate, this is because the equilibrium is a salient or focal point. If this is not the case, the equilibrium has to be approached in some way, and individuals have to form expectations about it. In Economics, several models try to explain the process of expectations formation and coordination by analysing the reasoning mechanism used by individuals. Individuals may either hold perfect expectations about what is going to happen, or may not be able to form accurate expectations. For example, this is taken into account in the bounded and perfect rationality literature. Evidence from real markets and from laboratory indicates that individuals are not likely to be perfectly rational in the sense of the REH introduced by Muth (1961). But there is also evidence on the fact that individuals *can* be perfect forecasters. We thus addressed in this chapter the question of how do people reason when they form expectations and how can imperfect rational agents have perfect forecasts.

We therefore stressed that, when rationality is limited, it can be the consequence of involuntary or voluntary restrictions. In that sense, we have to explain the mechanisms of the reasoning process and its stopping procedure. Here we focus our attention on *eductive* reasoning, that we define and put in relation with other types of reasoning and other concepts. Eductive learning is a sophisticated reasoning about a situation and about the reasoning of the opponents; therefore, it works through introspection and through one’s forecasts about the forecast of others. It occurs in people mind, in notional time, and thus is different from evolutive procedures run in real time through adaptation. It is based and strongly connected to the notion of common knowledge, as being the internal process allowing the depth of knowledge to increase. It occurs in iterative steps and is likely to stop because of some constraints. Such constraints take into account information processing costs and cognitive abilities. These two elements determine the moment when the possibly infinite regression of an eductive type of reasoning becomes finite. Agents with low cognitive abilities will involuntary stop this process at the step corresponding to their cognitive constraint. Agents with high cognitive abilities will voluntary stop sophisticating when one additional step will not bring them a sufficient outcome compared to the cost involved in thier effort, and given the beliefs they hold about the reasoning processes run by the opponents. It is more interesting for them not to go to the infinitum, but just to stop one step ahead on the others.

Eductive reasoning is a complex (difficult) reasoning; therefore, it is important to examine the conditions likely to favour it. In particular, some stabilizing situations may favour the success of eductive reasoning and especially guarantee the fact that at some stopping point in the reasoning process, the equilibrium may still be attained (the system is not too far from the equilibrium). The situation that we take into account is the negative feedback situation; in this context, any deviation is counterbalanced by an opposite one that ensures the stability in the system. Moreover, this is the context that people face when dealing with price expectations, numbers…etc, because, as psychological research shows, numbers are perceived through oscillatory scanning on a oriented scale. In this context, the moment when the eductive mechanism stops, may coincide with the moment at which reflective beliefs become intuitive. When this is the case, agents *jump* directly to the equilibrium and (limited) eductive reasoning is successful.

# Part I

# Investigating eductive abilities: an approach through beauty contest games with negative feedback

## Contents

# Chapter 2

# Beauty contest games with negative feedback

## 2.1. Introduction

Experiments on guessing games have become popular in the last decade, especially for investigating different learning models (Nagel,1995, Ho et al.,1998), and assumptions about reasoning behaviour (Camerer,2003). The success of these experiments relies on the fact that they respond to the need to test two closely related issues in economic theory : first, most of the models used to describe market activity rely on the theoretical assumption that agents are substantively rational, possessing the ability to solve almost instantaneously the most complex inference problems to take a decision ; second, many models of economic behaviour are based on the hypothesis that, when choosing a strategy, agents maximize their utility under the assumption that all other agents behave in a similar way, i.e; under the assumption of common knowledge of their rationality. These assumptions are used to model expectations formation by rational agents.

The rational expectation hypothesis is considered as the extension of rationality to expectation formation (Muth,1961). Following Binmore's(1987) terminology, the rational expectations hypothesis relies both on "eductive" and "evolutive" justifications. Evolutive arguments, offered by the repetition of the situation, are inherent to experiments where subjects are asked to take repeatedly analogous decisions. Repetition provides also a basis for observing the success of eductive learning. Eductive learning, which takes place in notional time, is, as emphasized by Guesnerie(1992), a necessary but not sufficient condition for the success of the evolutive convergence. That means that the conditions of instantaneous success of eductive learning or asymptotic evolutive learning are the same (both processes lead to the same sequence of results in a game). Eductive learning relies on the mental activity of agents who "forecast the forecast of others", by understanding the logic of the situation, i.e. they use sophisticated reasoning rules to "guess" the equilibrium. Guessing games are a simple tool for testing the validity and the depth of this type of "instantaneous" complex introspection.

The maximization issue implies that all agents are equally rational, thus the former type of introspection is collective: all agents believe that all agents believe that…all agents are able to use the same kind of eductive reasoning when "guessing" the equilibrium.

The basic idea underlying the guessing game was first introduced by Keynes(1936), in his famous metaphor about beauty contests: there are traders who "devote [their] intelligences to anticipate what average opinion expects average opinion to be. And there are some, I believe, who practice the fourth, fifth and higher degrees", exactly as in a game where one is prompted to choose the prettiest girl from one hundred faces; one's will not choose the girl one's really like, not even the girl one's think the others like, but the girl one's think the others think the others think…as being the prettiest.[1]

The rules of the beauty contest game (BCG) are simple (Nagel,1995). $M$ players have to choose simultaneously a number from a closed interval $[l, h]$. A frequently studied case is $l = 0$ and $h = 100$. The winner is the player whose choice is closest to $p$ times the mean of all chosen numbers, where $p$ is a predetermined number, usually smaller than one. The winner gains a fixed prize, which is split among all winners if there are several. In an experiment, the

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[1] Thereafter the basic game under scrutiny indifferently is cited as guessing game, beauty contest game (BCG) or average game (Moulin, 1986, first introduced this game under the latter term). In this paper we will equally use the two first denominations.

game can be repeated several times within the same group, to allow subjects to learn. The parameter $p$ captures the idea that in a guessing game, agents do not act exactly as described by Keynes' beauty contest game (where $p = 1$), but that agents want to be a little bit away from the mean. As an example, professional investors are concerned with acting around the average selling time, but just before the others ($p<1$) (Ho and al.(1998)).

Assume that an investor intends to "sell high" and to "buy low". To be successful he must sell shortly before the other investors sell, when the price is at its highest level. This implies a guess about the time when other investors start selling, to avoid selling during the crash. Similarly, an investor wishes to buy at the lowest price, i.e. just a little before the other investors start buying and pushing the price upwards. Translated into a beauty contest game, this is equivalent to choosing a high number when the mean is expected to be low ("crash" expected), and choosing a low number when the mean is expected to be high ("bubble" expected). In such a game, eductive reasoning implies negative feedback in contrast to the ordinary beauty contest game which involves positive feedback. Positive feedback means that an agent who guesses a high mean announces a (relatively) high number and an agent who guesses a low mean announces a (relatively) low number. With negative feedback, guessing a high mean implies announcing a low value and guessing a low mean requires announcing a high number. The case of crop producers provides a nice illustration: if all producers expect a high price, the market price will be low because a high price expectation will lead to high production levels. Similarly, if producers expect a low price, the market price will be high because of demand shortage.

Introducing negative feedback modifies the basic beauty contest game in two ways: it affects the convergence process to the equilibrium solution, and affects the location of the equilibrium solution.

In the positive feedback BCG both the eductive reasoning process and the evolutionary dynamic process, converge to the rational expectations equilibrium monotonically. For example, in the game for which numbers are chosen between 0 and 100 with $p < 1$, the process begins with a high value and converges monotonically towards 0. In contrast, with negative feedback, the convergence to the equilibrium point is described by a non-monotonic damped oscillating function (that is, a function that approaches the equilibrium solution by oscillating up and down around the equilibrium with decreasing amplitude). This process is of course only possible if there is an interior equilibrium, instead of a boundary equilibrium as in the standard BCG. Interior equilibria have been investigated ealier by Camerer and al.(1988) and by Guth and al.(2002), but under monotonic convergence, i.e. with a positive feedback structure[2]. Thus we will refer to our variant of the beauty contest game as "beauty contest games with negative feedback and interior equilibria".

Our modification to the basic beauty contest game allows to explore several issues. Typically, as pointed out by Guth and al.(2002), interior equilibrium beauty contest games exhibit smaller deviations from the equilibrium event in first round choices. A preliminary question is whether the same result will be observed in games with a negative feedback structure (in which the REE doesn't correspond to a focal point). Furthermore, with an alternating elimination of dominated strategies, convergence to the equilibrium solution might be faster, by reducing the anchoring bias on the previous value (Tversky and Kahneman, 1974), typically observed in standard beauty contest games. An important reason why negative feedback might generate smaller deviations and faster convergence to equilibrium, is a stabilization effect. The stabilization effect is due to the fact that any deviation in one direction will be partially offset by a deviation in the other direction. It is well known that negative feedback tends to stabilize the economy because any major change will be offset by the very reactions they generate (Arthur, 1990). The same effect applies to the BCG. Our variant of the beauty contest game generates a convergence process by which intervals are deleted on both sides of the equilibrium point, which allows a more accurate location of the equilibrium, even by individuals who apply only two steps of reasoning. In contrast, after two steps of reasoning in the standard BCG, subjects are not able to locate as accurately the equilibrium point. The reason, as we show, is that two sided elimination provides "more information" than one-sided reduction because with two-sided reduction the choice interval is "scanned" several times, which makes it computationally easier for subjects to locate the equilibrium solution. More generally, actions generating negative feedback lead to a more predictable outcome.

This chapter is organized as follows: in section 2.2 we theoretically describe the BCG with negative feedback. Section 2.3 reviews the previous experimental literature on the BCG. Section 2.4 presents a market application for the BCG with negative feedback and section 2.5 concludes.

[2] The winning number in their design is $p \times (c + mean)$).

### 2.3. Theoretical characterization of the beauty contest game with negative feedback

A large number (*M)* of players simultaneously have to choose a number from a closed interval *[l,h]*. We set the bounds at $l = 0$ and $h = 100$ as in the standard BCG. The game might be played repeatedly (in several rounds). The winner of a round is the player whose chosen number is closest to:

$$q - p\ \bar{x}$$

where $q$ is parameter whose value is set equal to 100 (or $q = h$), $p$ is a constant ( $p < 1$) and $\bar{x}$ is the *mean* of all chosen numbers within a round, i.e. $\bar{x} = (x_1 + x_2 + \ldots + x_M)/M$. This game is isomorphic to the basic game proposed by Nagel (1995) where the restrictions on the choice space and $p$ are identical, but the target number is $p\bar{x}$.[3] At the Nash equilibrium, every player should symmetrically play the winning number $w$ such as $w = q - pw$, thus the Nash equilibrium of this game is $w = \dfrac{q}{1+p}$.

### 1.2.1. Eductive reasoning: iterated elimination of dominated strategies

We study the associated thought processes, as in the standard game. Here the process of thought under scrutiny is eductive reasoning (Guesnerie, 1992). The eductive reasoning takes place in notional time (in people's mind rather than in real time) following several steps of reasoning. Let us call the original choice interval $I_o = [l,h]$.

*Step 1*: at notional time $t = 0$, each player realizes that the mean cannot be larger than $b_0 = h$; thus the winning number will be larger than $b_1 = q - ph$. Step 1 generates therefore an intermediary interval containing weakly dominating strategies $I_1 = [b_1, b_0]$. Strategies below $b_1$ are deleted.

*Step 2*: at notional time $t = 1$, each player knows that his opponents will only submit numbers that are larger than $b_1$; thus the winning number will be smaller than $b_2 = q - pb_1 = q - p(q - ph))$. This generates a new interval $I_2 = [b_1, b_2]$ and strategies larger than $b_2$ are eliminated.

.....*(the process continues)*

[3] The game has the same structure, but a different mathematical composition.

*Step n*: at notional time $t = n - 1$, each player knows the result of the previous step, i.e. $b_{n-1}$, $b_{n-2}$, and the interval $I_{n-1}$, so the bound generated in step $n$ is $b_n = q - pb_{n-1}$. More precisely $b_n = q\frac{1-(-1)^n p^n}{1+p} + (-1)^n p^n h$. If $n \to \infty$, the corresponding interval $I_n$ is confounded with this point (lower and upper limits converge to the same value).

In this process $I_i$ is an intermediary dominating strategies interval. As $i$ increases, the set of dominating strategies becomes smaller and intervals $I_i$ narrows down through the eductive equilibrium. Figure 2.1 illustrates the iteration process for the first three steps.

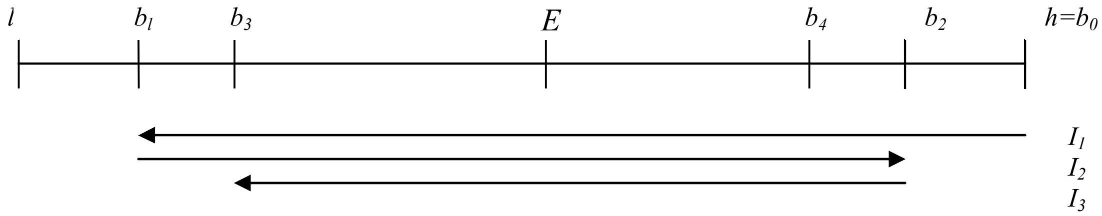



Figure 2.1.Iterations in beauty contest games with negative feedback

A unique equilibrium, which coincides with the Nash equilibrium, is reached through eductive reasoning. It occurs after an infinite process of elimination of dominated strategies:

$$\lim_{n\to\infty}\left[q\frac{1-(-1)^n p^n}{1+p} + (-1)^n p^n h\right] = \frac{q}{1+p},$$

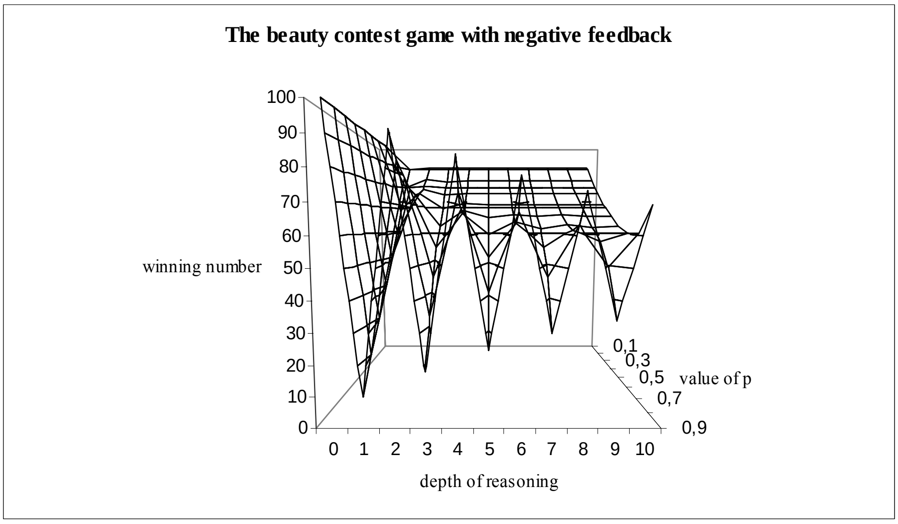
if $p<1$, which is the stability condition.

### 1.2.2. Characterisation

The BCG with negative feedback is characterized by its isomorphism to Nagel's (1995) games, its interior solution and its negative feedback.

The sequence of bounds generated by the eductive reasoning in this game is, as described earlier, $h$, $q-ph$, $q-p(q-ph))$, …, $q\frac{1-(-1)^n p^n}{1+p} + (-1)^n p^n h$.

Remember that in Nagel’s (1995) game, the corresponding sequence is $h, ph, p^2h, \ldots p^n h$. Both games are stable under the condition $p<1$ and have a unique rational expectation equilibrium, which is the limit value of the sequences when $n \to \infty$. The following graph presents the structure of the BCG with negative feedback for each decimal value of $p<1$ and for each iteration step up to 10.



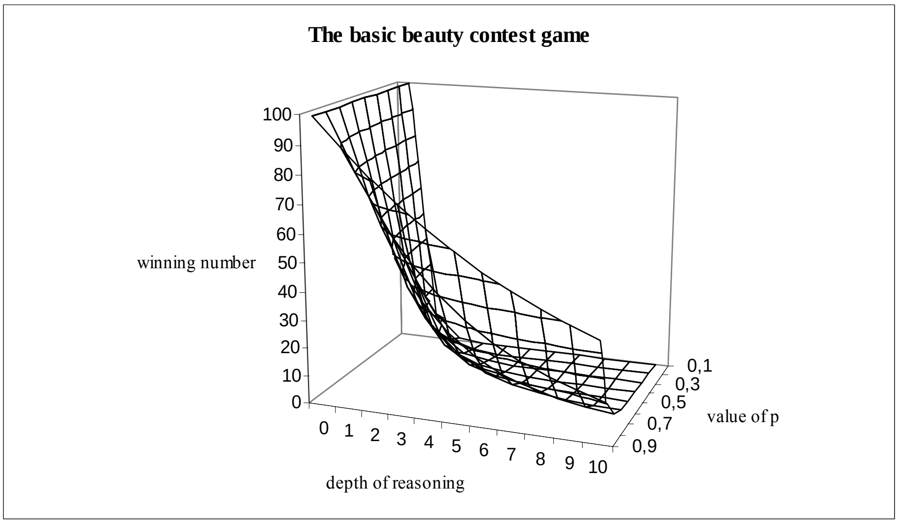




Figure 2.2.The beauty contest game with negative feedback and the basic BCG (winning number as a function of the depth of reasoning and the value of *p*)

In section 1.2.1, we calculated successive bounds which correspond to higher levels of eductive reasoning. From these calculations and from figure 2.1 it was already visible that all odd bounds ($b_{2k+1}$) are inferior to even bounds ($b_{2k}$) and, within a category, $b_{2k-1} < b_{2k+1}$ and $b_{2k} > b_{2k+2}$. This characterizes a non-monotonic damped oscillating function (i.e. a function that approaches equilibrium by oscillating up and down around the equilibrium with decreasing amplitude), as visible on figure 2.2 (non-monotonic left-to-right lines).

The characteristics of this function imply that up inflexion points correspond to even depths of reasoning, while down inflexion points are related to an odd depth of reasoning. A BCG has an interior game theoretical solution $s_t$ in period $t$ if $l < s_t < h$, which is the case for our variant[4].

The more steps of reasoning are implemented in a BCG, the narrower is the remaining choice interval. The sequence of narrowing down intervals is $I_0 \supseteq I_1 \supseteq I_2 \supseteq \ldots \supseteq I_n$. Although the process described above arises in notional time, we shall call *speed of convergence* the parameter describing the evolution from interval $k$ to interval $k+1$, for $k \in [0,n]$. The *speed of convergence* measures the percentage of reduction of the interval containing the equilibrium solution, and will be denoted by $v_t$; $v_t$ is equal to the ratio of the width of interval $k+1$ and the width of the previous interval $k$, i.e. $v_k = \dfrac{\|I_{k+1}\|}{\|I_k\|}$.[5] Thus for any type of BCG the theoretical speed of convergence $v_t$ is constant and $\forall t>1,\ v_t = p$. Moreover, when $h = q$, the two sequences coincide.

## 2.3. Previous literature on guessing games

The game was first introduced by Moulin (1986) and experimentally tested in classroom by Guesnerie. Nagel (1998) and Camerer (2003) provide complete surveys on previous work on

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[4] As this solution in the BCG with negative feedback is $\dfrac{q}{1+p}$, as $p < 1$, then $h > \dfrac{q}{1+p} > \dfrac{q}{1+1} = \dfrac{q}{2} > l$ if $q < 2h$ and $2l < q$. This is true for the particular case when $q = h$ and $l = 0$. This solution is *high* when $p < 1$ (here $\dfrac{q}{2} = \dfrac{l+h}{2} < s_t < h$). As $l \leq mean \leq h$, $p\, l \leq pmean \leq ph$, $l \leq q - ph \leq q - pmean \leq q - pl \leq h$ if $0 \leq \dfrac{q-h}{l} \leq p \leq \dfrac{q-l}{h} \leq 1$, which is the case for $q = h$ and $l = 0$. Moreover, any empirical solution $s_t = q - pmean_t$ is interior as long as $p$ is a probability.

[5] The sequences of embedded intervals are respectively :

| | |
|---|---|
| $\|I_0\| = h$ | $\|I_0\| = h$ |
| $\|I_1\| = ph$ | $\|I_1\| = p^0[h(1+p) - q]$ |
| $\|I_2\| = p^2h$ | $\|I_2\| = p^1[h(1+p) - q]$ |
| … | … |
| $\|I_n\| = p^nh$ | $\|I_n\| = p^{n-1}[h(1+p) - q]$ |
| *(positive feedback BCG)* | *(negative feedback BCG)* |

monotonic boundary and interior equilibria beauty contest games. Their reviews are structured according to the main model used to explain behaviour in BCG. Reasoning levels seldom exceed 2 steps. Other related experimental literature includes Guth and al. (2002), who introduce not only interior equilibria but also heterogeneous players. They observe faster and closer convergence to the game-theoretic solution with an interior equilibrium and with homogenous players[6]. Weber (2001), analyzes basic boundary equilibria guessing games with no communication of results between rounds. In his experiments, while there is less learning under no the non-communication condition than when outcomes are revealed, there is convergence towards the equilibrium prediction. Kocher and Sutter(2000), who analyze individual versus team behaviour in basic games, find that groups learn faster and outperform individuals in terms of payoffs. Other contributions to the study of beauty contest games are theoretical, like Lopez (2001), who fully characterizes from a game theoretical point of view the basic beauty contest game, and Branas and Morales (2002), who provide simulations in order to explain the "confusion in unravelling" stressed by classical interpretation of basic beauty contest games results. To our knowledge, non-monotonic convergence in BCG with interior equilibria[7] has not been studied earlier. Nevertheless, we shortly review below several of these papers dedicated to beauty contests, in order to remind some of the analyses that have been done on results interpretation and some of the variations on the basic setting that we will subsequently use in the analysis of our experimental results in this part of the thesis or in the second part. For each paper, we indicate the main assumptions that it aimed at testing and major findings in results interpretation.

### 2.3.1. Nagel (1995), Duffy and Nagel (1997), Domesch and al. (2004)

After having played as a participant the Guesnerie's game in classroom, Nagel was the first who experimentally tested and interpreted results on guessing games in several papers. Nagel first paper (1995) tested several values of $p$ in what we call the basic beauty contest game: players in groups have to choose numbers from a closed interval and the winner is the person whose choice is the closest to $p$ times the group mean. The paper particularly addressed *the question whether a simple iterated best-reply model, $50p^k$, $k=1,2\ldots n$, could account for first period behaviour and if players were using higher reasoning steps over time and learning*

[6] Their REE is set at 50, which corresponds to a focal point.

[7] Only complex market games, which are isomorphous to our variant of the beauty contest game (for example cobweb games) have been tested experimentally.

*direction theory* ( Selten and Buchta, 1994) *could structure the data*. Experiments took place for four rounds within groups of 15-18 subjects. In order to classify data, Nagel specified neighbourhood intervals around values given by $50p^k$, $k=1,2\ldots n$ and tested whether participants' first period choices are rather close to these points. The behaviour in the remaining 3 periods was investigated by evaluating the adjustment process that participants employ using their individual experience. Nagel calculates a parameter called the adjustment factor, defined as the relative deviation from the mean of the previous period (for period 1 the initial reference point is 50). This factor is compared to the retrospective optimal adjustment factor defined as the optimal deviation from the mean of the previous period that leads to exactly the winning number, i.e. $p$ times the mean of the current period. *Her results suggest that many players do not choose numbers at random but instead play approximately optimally, given the behaviour of the others (in which 1 or 2 steps of reasoning are exhibited) and are influenced by the parameter p of the game. No support for the hypothesis of an increasing in the depth of reasoning with time is found, but learning direction theory provides a good explanation of guesses.*

In a joined paper with Duffy (1997), Nagel addressed the question of the influence of a single player on aggregated performance by changing the *mean* of the basic game into *maximum* or *median*, with $p = ½$: *are players more concerned in the median game with market fundamentals and less with speculation about actions of other players? Are players concerned with outliers (who choose high numbers) actions in the maximum game?* They find evidence suggesting that the percentage change in guessing over rounds in the direction of the *REE is significantly larger in the median game* than in the mean game, and strong support for *high guesses in the maximum game*.

Domenesch and al.(2004) provided a finite mixture analysis of beauty contest data from multiple sample: they present a statistical analysis allowing for unobserved heterogeneity (through the reasoning level) and manifest heterogeneity (group membership). The analysis is based on a model of censored and truncated normal distributions plus a uniform distribution, without imposing any structures on the model specification. A key result is that individuals playing BCG share a *common pattern of reasoning*, independently of the specific set-up of the experiment, but there is *substantial variation across groups of the proportion of subjects using different levels of reasoning*.

### 2.3.2. Thaler (1997), Bosch and Nagel (1997), Nagel and Selten (1998)

The authors independently designed and announced an experiment on the BCG with $p = ⅔$ in different daily business newspapers, which allowed them to play the game with large pools of subjects. All choices distributions showed spikes at 33.33, 22.22, and 0. They note that almost all subjects who provided comments describing their *reasoning process only mentioned levels 0, 1, 2, 3, and level* $\infty$. 18% of choices were at the REE.

### 2.3.3. Stahl (1996,1998)

Stahl (1996) *combined Nagel's step-k model of bounded rationality with a law of effect learning model*. Initial disposition to learning are heterogeneous, but rates of learning are homogeneous. Players begin with a disposition to use one of the step-*k* rules of behaviour, and over time they learn how the available rules perform and switch to better performing rules: while over a third of the population begins with random play, they quickly abandon that rule for a step-2 rule. This is interpreted, in contrast to Nagel (1995), as a proof for *increasing depth of reasoning with time*. Bayesian rule-learning is strongly rejected.
Stahl's next paper (1998) addressed the question of *integer or continuous step rules* in thinking processes. They found that introducing non-integer steps doesn't better explain the data and interpreted *the integer steps model as a fact of human nature*.

### 2.3.4. Ho and al. (1998), Camerer and al. (1998, 2003)

When Ho and al. (1998) replicated Nagel experiments, they introduced three variants in the experimental setting: they first tested infinite (as the basic BCG) versus finite threshold games (in which then number of iterations to reach the REE is finite); second, they compared small groups to large groups; finally, they run experiments with experienced/inexperienced participants. These modifications allowed them to address different questions: *i) Is the convergence process faster when groups are smaller? ii) Are participants better in hitting the REE when the number of theoretical iterations is finite? iii) Are players who have already tested a version of the game behave differently from inexperienced players?* For results interpretation, they tested an iterative best-reply model against various others. Their main general results were:

i) *First-period choices are widely distributed and far from equilibrium, but convergence enhance after in subsequent periods.*

ii) *First-period choices are consistent with a median of 2 steps of iterated dominance in the infinite-threshold game, and one step in the finite-threshold game.*

iii) *Choices after the first period are consistent with 70% of the subjects best-responding to a weighted sum of previous target numbers.*

iv) *All parameters estimates are sensitive to p, the group size and whether subjects played a similar game before.*

Moreover, *v) convergence is faster in finite-threshold games than in infinite-threshold games; vi) convergence is also faster in large groups than in small groups;* and *vii) it is not improved in experienced groups.*

In order to take into account the reasoning map within a population, Camerer and Ho (2003) construct a cognitive hierarchy model that they apply to various games. This model is easily exploitable to interpret first round results in BCG. In this model, the authors take into account the fact that limited strategic reasoning results from constraints on the human brain. The "cognitive hierarchy" (CH) model allows to a fraction of players to randomize equally across strategies (they correspond to 0-step players). Higher step players believe all other players use only inferior steps of thinking. They assume a normalized true distribution for the *k*-type's beliefs about the proportions of lower-step types that *k*-step thinkers use to compute expected payoffs and choose best-responses. A single parameter function is chosen (the Poisson distribution), as more and more thinking steps are increasingly rare: players may have working memory constraints and doubts about rationality of others. We will explain this model analytically in Chapter 3 and Chapter 4 as we will use it to interpret our results and slightly modify it.

Various games have been reanalysed by Camerer and Ho (1999) within an *experienced-weighted attraction* (EWA) model. In this model, players update their probability distribution of strategies according to the payoff received for their actual choice. *But strategies that have not been chosen are also reinforced if they were in the neighbourhood of past winning numbers.* In a functional-EWA method (2002), fixed parameters have been replaced with functions of experience, allowing both individual differences in learning styles *and* endogenous cross-game differences: a change detector is introduced and accounts for equilibration and surprise.

### 2.3.5. Kaplan and Ruffle (2000)

This paper uses the context of a variant of the BCG in order to try to control for strategic behaviour (Haman effects), and isolates the self-serving bias. The main goal of the authors is not to test an iterative reasoning behaviour; nevertheless, their results can be used to point out an environment in which BCG results can be improved. The self-serving bias that they measure concerns beliefs about the rationality of others. They modify the guessing game in a way that allows *testing for biased beliefs about the rationality of others*. In addition to paying a fixed prize to the subject whose guess is closest to ⅔ times the average of all guesses, as in the basic BCG design, their design pays a variable payoff to each subject. There are 30 subjects in each session, each subject with an identity number from 1 to 30. Those subjects with an odd identity number receive as a variable payoff the mean guess of all 29 other chosen numbers divided by four. All even-numbered subjects receive 100 minus the mean guess of all 29 other subjects, this number divided by four. By excluding a subject's guess from his variable payoff, they control for strategically manipulated guesses but also introduce a circularity operator in the environment, which helps connecting participants. A subject's guess summarizes his beliefs about everyone else's guesses. They find very limited support for the existence of the bias and *results which are very close to those obtained in the basic BCG (in the mean), but which are very concentrated (with very low standard deviations), which stands for strong beliefs coordination.*

### 2.3.6. Kocher and Sutter (2000)

The paper compares behaviour of individuals and small teams in the context of BCG. The main purpose of this paper is to address two basic questions: *i) Does it make a difference in outcomes with regard to the iterated elimination of dominated strategies, whether individuals or small teams compete against each other? ii) Is there a difference in dynamic learning processes between individuals and small teams?* The article lists several reasons for expecting teams and individuals to behave differently in a dynamic setting: in social psychology research teams are assumed to be more competitive or aggressive than individuals (Bornstein and Yaniv, 1998); more rational (through team discussion, faster understanding of the strategic situation of a game, cross-forecasting). Therefore, teams should converge faster to the game theoretic solution and apply deeper levels of reasoning immediately after the first round of experience with the game. Their findings *i) do not lend support to the view that teams are more rational players* in the sense that they have deeper levels of reasoning than individuals per se. First round behaviour with respect to rationality is uniform across the individual and the team treatments; *ii)* however, in the course of the experiment, *teams increase their depth of reasoning*; *iii) the learning direction theory of Selten and Stoecker (1986) is a good predictor for both individual and team behaviour.*

### 2.3.7. Weber(2001)

The experiments in Weber's paper consisted in several designs with alternative information and results communication conditions. In particular, he wanted to test the role of learning through observation of outcomes and reinforcement resulting from payoffs and thus hypothesised that *with no feedback on previous period results, choices should not converge towards the Nash equilibrium through repeated play*. The basic $p = 2/3$ game was tested, under different communication and information conditions, starting from control sessions (with full information on past results) and gradually reducing results communication until the null information treatment. While he found less learning under no communication than when outcomes are revealed, *there is convergence towards the equilibrium prediction and intermediary information designs do not induce significant differences*. The results are interpreted as a strong validation for the possibility that *people can learn simply through repeated experience with an environment*.

### 2.3.8. Branas and Morales (2002)

This paper presents a pre-experimental view of the BCG, as the analysis is conducted through simulations. Authors simulated a BCG experiment in which they controlled for the reasoning skills of subjects. They eliminated heterogeneity among players in reasoning levels, but allowed for heterogeneity in computational skills, i.e. the capacity to calculate with digits. They showed that *the lesser computational skills, the better guess and the faster convergence to the equilibrium*.

### 2.3.9. Guth and al. (2002)

Their paper studies behaviour in BCG with interior equilibrium and heterogeneous players as compared to basic BCG with boundary equilibrium and homogeneous players. The experimental design introduces continuous payoffs (not only the winner is paid, but all participants, according to the quality of their choices) and interior equilibrium as in Camerer and Ho (1998). They also explore convergence with heterogeneous players by setting two targets instead of one, i.e. all players do not have to approach the same winning number. They motivated these modifications as closer to financial decision situations, in which dichotomous payoffs, boundary equilibria and perfectly symmetric incentives rarely exist. *Their design aimed to explore, first, whether deviations from the REE are smaller in the first round than in the basic BCG; second, if the introduction of heterogeneous players forces participants to think harder about other players' behaviour and thus allows them to better understand the game; third, if the payment scheme will induce slightly smaller deviations from optimality*. They tested a stranger design with groups of 4 persons interacting for 10 rounds. The winner was the player whose choice was the closest to $p\times(c+mean)$, with $c$ a constant. Besides control treatments, in which the basic BCG was replicated, parameters were set as follows: $p$ value was configured for two designs, one with $p = ½$ and another in which heterogeneity was introduced through $p$ as for half of the participants it took the value ⅓ and for the other half ⅔. In homogeneous settings, $c = 50$. *Convergence to the equilibrium was swifter* (but their interior equilibrium 50 is a focal point) and *heterogeneity was detrimental for profits and convergence*.

### 2.3.10. Costa-Gomez and Crawford (2004)

In this paper experiments that elicit subjects' initial responses to several dominance-solvable two-person guessing games (among which BCG) are reported. The data from these experiments have been analyzed using a variety of bounded rational strategic decision rules called types: leading examples include $L_1$ (for level 1), which chooses its best response given a uniform prior over its partner's decisions; $L_2$, which best responds to $L_1$; $L_3$, which best responds to $L_2$; $D_1$ (for dominance 1), which does one round of deletion of dominated decisions and chooses its best response given a uniform prior over its partner's remaining decisions; and $D_2$, which does two rounds of iterated deletion of dominated decisions and best responds given a uniform prior over the remaining decisions. The structure of a game is publicly announced, except for varying payoff parameters, to which subjects are given free access, game by game, through an interface that records their information searches, in order to study cognition: in the light of the cognitive implications of alternative theories of behaviour, *to better identify the decision rules and mental models that underlie their initial responses; and to learn to what extent monitoring search helps to identify subjects' types and predict their deviations from equilibrium decisions*. Many subjects' decisions and searches show clearly that they understand the games and seek to maximize their payoffs, but have bounded rational models of others' decisions, which lead to systematic deviations from equilibrium. Because their types specify precise guesses in large strategy spaces, the identifications show that those subjects had accurate models of the games and acted as rational, self-interested expected-payoff maximizers. $L_k$ types are overwhelmingly predominant, and more natural than $D_k$ and other types. This lends support to the *leading role given iterated best responses* in informal analyses of strategic behaviour.

### 2.3.11. De Giorgi and Reimann (2003, 2004), Reimann (2004)

In order to provide an explanation for typical patterns observed in real data (as strictly positive outcomes in the one-shot game, the skew background distribution of guessed numbers, the polynomial convergence towards the REE), these papers aim at testing two assumptions: *i) players consider intervals rather than exact numbers to cope with incomplete knowledge* and *ii) players iteratively update their recent guesses.* They propose a mechanics-inspired model in which they take into account a particular reasoning process in which they include a hypothetical errors distribution in guesses and a confidence parameter for a guess. Basic game theoretical equations which stand for the iterative reasoning process are rewritten by replacing exact bounds with intervals and by adding a confidence measure on choices. The dynamics of the process is analysed as an adiabatical process in which authors particularly explain why chosen numbers are strictly positive in the guessing game. The guessing game is thus classified as a *non-equilibrium game*: participants choices are not close to the REE because such a reasoning process simply doesn't converge to zero.

## 2.4. A market application for the beauty contest games with negative feedback

We designated in the introducing part of this chapter several economic situations which can be modelled through the negative feedback BCG: professional investment activity, crop production, etc. In this section we provide a geometrical proof of the equivalence between the BCG with negative feedback and a general cobweb market[8]. In order to do so, we alternatively iterate the negative feedback BCG starting from the high border of the definition interval[9] and replicate each iteration point. Therefore, abscises on the *Ox* axis are sequentially *h*, BCG(*h*), BCG(BCG(*h*)) etc…and to each *x* value correspond two *y* values, *x* and BCG(*x*), on the *Oy* axis. We connect consecutive points as (*x*,*x*), (*x*, BCG(*x*)), starting from the highest *x* to the lowest[10] and give a picture of them in figure 2.3. The plain convergent line connects all points as describes previously. The simple doted line is the first bisecting line, i.e. relies all points (*x*,*x*). The spot-mark line connects all (*x*, BCG(*x*)) points. Points on this line are collinear, as the slope of the line between any two points is the same. This slope is calculated (to the horizontal axis), as $\frac{b_n - b_{n-2}}{b_{n-3} - b_{n-1}}$ = -*p*, with previous notations[11], while the slope of the simple doted line is 1. The plain line converges only if $1/p > 1$ or $p < 1$, which is the BCG game convergence condition. As the first bisecting line is increasing it can be assimilated to the supply function, and the decreasing spot-mark line to the demand function. Therefore the convergence condition is the cobweb convergence condition, that we will extensively explain in Part II, i.e. (within an inverted axis system), the slope of the supply function should be smaller than the slope of the demand function. As a comparison, we present in figure 2.4. the positive feedback graph, which is constructed with the exactly same points sequence, and in which the convergence picture is different.

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[8] In Part II, Chapter 5, we also show this equivalence for the other direction of the equivalence (the implication from the cobweb model to the BCG with negative feedback).

[9] We denote BCG(*x*) the transformation of value *x* through the function 100-*px*.

[10] (*h*,*h*), (*h*,BCG(*h*)), (BCG(*h*),BCG(*h*), (BCG(*h*), BCG(BCG(*h*))) etc.

[11] $$\frac{b_n - b_{n-2}}{b_{n-3} - b_{n-1}} = \frac{q\frac{1-(-1)^n p^n}{1+p} + (-1)^n p^n h - q\frac{1-(-1)^{n-2} p^{n-2}}{1+p} - (-1)^{n-2} p^{n-2} h}{q\frac{1-(-1)^{n-3} p^{n-3}}{1+p} + (-1)^{n-3} p^{n-3} h - q\frac{1-(-1)^{n-1} p^{n-1}}{1+p} - (-1)^{n-1} p^{n-1} h}$$

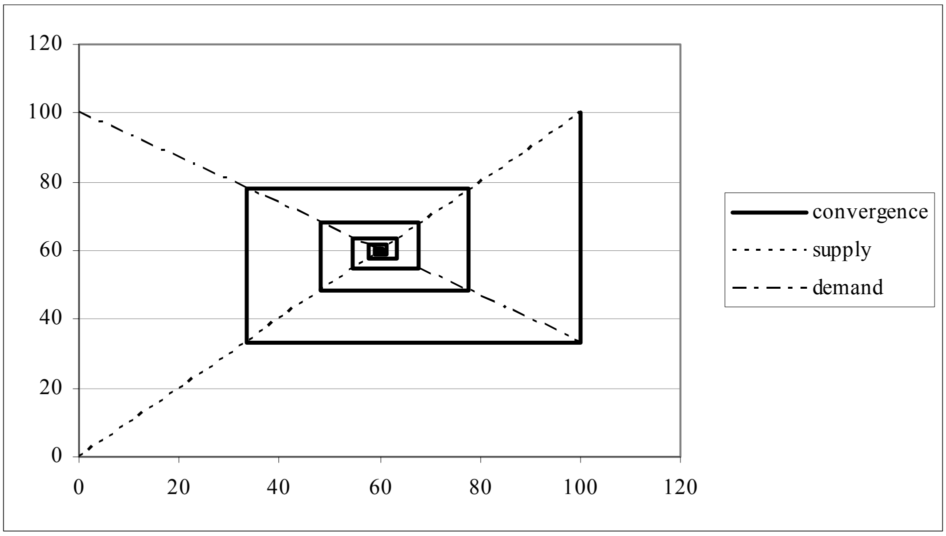


Figure 2.3. How to link BCG with negative feedback to the cobweb market

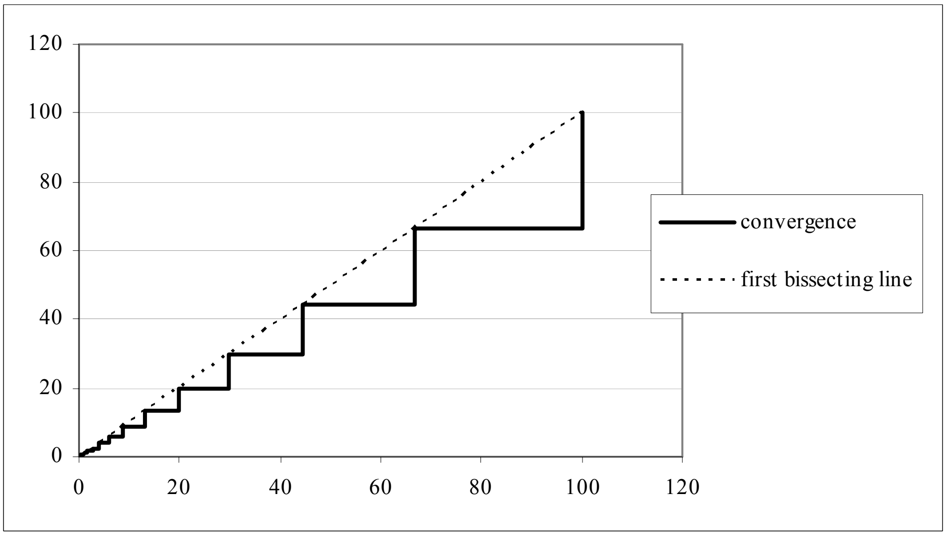


Figure 2.4. Convergence in the positive feedback BCG

## 2.5. Conclusion

Eductive reasoning is a complex type of reasoning. Its depth can be expressed in steps, as already stressed by Keynes (1936) in his metaphor about the beauty contest. Therefore, when the beauty contest was formalized into a simple guessing game[12] (Moulin, Guesnerie, Nagel), it served as an interesting tool to experimentally investigate the mechanism of the eductive reasoning. The main purpose in such research was to measure the extent of the implications which serve to switch from a step to another: how deep is the collective introspection about

[12] Participants have to guess numbers in some close interval and the winner is the one who is the closest to *pmean*. Keynes' example stands for $p$=1.

what "average opinion expects average opinion to be". The rank of the last eductive step performed by an agent determines his type. Trying to explain agent's typology, several authors experimentally tested the beauty contest game (among others, Nagel, Camerer, Güth, Reimann, Weber, Kaplan…). In experiments, the results sensibility with respect to several factors has been tested: variations in the convergence parameter *p*, in the size of the groups, in the location of the equilibrium (at the lower bound of the guessing interval, the upper bound[13] or at some interior point), in groups composition (experiences, inexperienced players, homogenous, heterogeneous). The analysis of the results provided similar results about the depth of reasoning and the strategies used by the players (about two levels of collective introspection, and winners relatively far from the equilibrium).

In this chapter we proposed an additional modification to the BCG: the introduction of negative feedback in the game structure, in order to be able to take into account economic situations as crop production or some aspects of professional investment. Introducing negative feedback modifies the basic beauty contest game in two ways: it affects the convergence process to the equilibrium solution, and affects the location of the equilibrium solution- the convergence to the equilibrium point is described by a non-monotonic damped oscillating function which limit is interior to the definition interval, rather than by an monotonic process driving the process at some bound. The game mathematical structure is described and put into perspective with the basic BCG. Our modification to the basic beauty contest game allows exploring several issues: does the interior equilibrium imply smaller deviations in first round choices? Is convergence faster when the feedback is negative (as dominated strategies are deleted on both sides of the equilibrium point, the environment is stabilized)? We theoretically answered these questions and we established a formal equivalence between our variant of the BCG and the linear cobweb model. In the following chapters, we will refer to beauty contest games with positive feedback (with corner or interior equilibrium) as BCG+ and to beauty contest games with negative feedback as BCG-. Comparisons between BCG+ and BCG- will be established. As BCG+ with corner equilibrium are considered "easier" than BCG+ with interior equilibrium in the sense that in the first game the equilibrium is a focal point (a boder), while in the later equilibrium is difficult to find, comparisons between BCG- and BCG+ are stronger when referred to BCG+ with corner equilibrium (*à la* Nagel).

[13] This also implied the convergence process to be finite rather than infinite.

**Contents**

# Chapter 3

# A one-shot experiment on eductive reasoning with negative feedback

## 3.1. Introduction

In the absence of an auctioneer, obtaining an equilibrium price on a competitive market remains partly an enigma. However, the theory of rational expectations provides a response on the type of reasoning leading to such an equilibrium. The reasoning, based on the eductive logic, consists in eliminating in a reiterated way the prices generated by dominated strategies. The concept of eductive reasoning was suggested by Binmore (1988) and considered by Guesnerie (1992) to justify the convergence towards the equilibrium price in the cobweb model. Referring to some specific configuration of the supply and demand functions, we can agree that agents coordinate on a single equilibrium. In other words the agents choose individual offers leading to the anticipated equilibrium price, knowing that this anticipation results from the iterated elimination of the dominated prices. But what is the result of this process when the beliefs of the agents are erroneous or when the eductive logic is only partially used by some agents? In this chapter we are interested precisely in a situation where each agent puts into practice an eductive reasoning of a limited and heterogeneous depth.

The beauty contest game offers a minimal and simple framework for tackling this question. Let us remember that in this game a large number of players ($M$) try to win a prize by simultaneously announcing a real number between 0 and 100. The winner is the player whose selected number is the closest to the average of all the numbers multiplied by a parameter $p$, with $p \in ]0, 1]$. In the event of an ex aequo, the prize is equally divided between winners. The game called "the beauty contest" corresponds in fact to the condition $p = 1$, and admits an infinity of equilibria. For $p < 1$, a unique equilibrium exists and corresponds to the situation of all players selecting 0. In fact, the highest mean of all chosen numbers can be 100; if all players were to choose 100, the winner would be a player whose choice is $p \times 100$. This leads to the elimination of all strategies in the dominated interval $] p \times 100, 100]$. If all agents choose $p \times 100$, the winner will be the one who announces $p \times (p \times 100) = p^2 \times 100$, and all strategies in $] p^2 \times 100,\ p \times 100]$ are eliminated. If all agents choose $p^2 \times 100$, the winner should choose $p \times (p^2 \times 100) = p^3 \times 100$, and all strategies in $] p^3 \times 100, p^2 \times 100]$ are dominated. The iterated use of this reasoning finally leads to select only 0 as a choice when the number of reasoning steps tends to infinitum. The 0 equilibrium is obtained under the hypothesis of an infinite depth of reasoning for all agents, which is also common knowledge.

This type of reasoning underlines many economic situations, where the agents must simultaneously make decisions, and whose result depends on the actions chosen by the others. For instance it is the case of the speculative markets, like the following example in Ho and al. (1998). On the stock exchange market, the possibility of making benefits depends mainly on choosing the best selling time. Let us consider the expectation about an increase in the price of a share. By anticipating the moment when the other agents sell, and the price going down brutally, each agent tries to sell shortly before the other investors' estimated selling time. The capacity to make profits for a trader will thus depend on its depth of reasoning. Let us suppose the current forecast: a share's price will go down on $D$-day. Then a rational agent of level 1 will sell on $D$-1. But if all the agents are rational of level 1, then the "crack" actually occurs on $D$-1. An agent with a depth of reasoning of level 2, will thus sell on $D$-2, because he anticipates that the crack will occur on $D$-1. But if all the agents have a depth of reasoning of level 2, the crack occurs on $D$-2, and an agent with a depth of reasoning of level 3 is brought to sell on $D$-3, etc...

The experiments on this type of game showed that the majority of the subjects announced numbers corresponding to a depth of reasoning of level 1 or 2. Only a minority exceeds this level. The winner is the player with the higher depth of reasoning and with the best estimation of the subjects' proportion corresponding to each depth of reasoning lower than his. The cognitive hierarchy model allows estimating this proportion accounting for the distribution of the numbers announced by the subjects in the experiments. But the heterogeneity in the depth of reasoning is not the only reason for announced numbers to be far away from the equilibrium. The types of beauty contests studied until now have a particular structure that we can describe as positive feedback. In a positive feedback game, announcing a "high" number is a best response to a high average. For example, if $p = 2/3$, an agent anticipating the average of the numbers to be equal to 60 will announce 40. The reverse situation happens in a negative feedback game: an agent anticipating a high average may find it beneficial to announce a low number, and on the contrary, an agent anticipating a weak average may find it beneficial to announce a high number. In the case of a number choice in the interval [0,100], a negative feedback game can be built by defining the winner as the player whose announced number is closest to $100 - p\times$mean, with $p < 1$.

Within a negative feedback framework, the process of iterated elimination of the dominated strategies is modified. Let us recall that in a positive feedback situation, the use of iterated dominance consists of successively eliminating the highest numbers in the intermediary dominating strategies interval. This process thus leads the agent to mentally explore only a part of the whole space of the strategies, in an asymmetrical way. The asymmetry of this process can make it difficult to localize the equilibrium, when the depth of reasoning is limited. In the case of negative feedback, the use of iterated dominance makes it possible to alternatively eliminate the higher and the lower part of the strategies interval. When doing so, the agent mentally explores all the space of the strategies, in a symmetrical way, and locates equilibrium more easily, even with a limited depth of reasoning. Thus, following the work of Arthur (1990), we make the assumption that a negative feedback environment, by its stabilizing properties, allows reaching the equilibrium of rational expectations more easily and faster than in a situation with positive feedback, even under the constraint of homogeneity of the processes of reasoning used in the two types of situations.

In this chapter we experimentally explore this hypothesis starting from a negative feedback beauty contest game. Our main result is that the numbers announced by the subjects are on average closer to the equilibrium in the negative feedback case than in the positive feedback one. We also show that this result cannot be explained by the differences in the depth of reasoning, because the depth of reasoning estimated within a model of cognitive hierarchy is identical to that obtained for a positive feedback game. Finally, we validate these results on the basis of simulations within a population of heterogeneous agents in terms of depth of reasoning.

We first remind the theoretical background of our experiment (3.2); we then describe our experimental design (3.3); the section 3.4 is dedicated to the comment of our results; our conclusions are presented in the last part of this chapter (3.5).

### 3.2. Theoretical background

$M$ players simultaneously choose a number in the interval [0,100]. The game is played only once. The winner is the player whose choice is the closest to the target $100 - p\bar{x}$, where $p$ is a constant ( $p < 1$), and $\bar{x}$ is the average of all chosen numbers: $\bar{x} = (x_1 + x_2 + \ldots + x_M)/M$.

We make the assumption that the agents use an eductive reasoning by eliminating the dominated strategies in an iterated way. The eductive reasoning takes place in notional time, i.e. instantaneously (Guesnerie, 1992).

*Step* 1: at notional time $t = 0$, each player realizes that the average cannot exceed the value $b_0 = 100$. This results in eliminating all the numbers ranging from 0 to $100 - p\times100$. Indeed, the value of the winning number cannot be lower than $b_1 = 100 - p\times100$. This lower limit generates a new interval $I_1 = [b_1, b_0]$, which includes the weakly dominant strategies, after the elimination of the strategies lower than $b_1$.

*Step* 2: at notional time $t = 1$, each player knows the conclusion of *step* 1, and consequently that the other players will only select numbers higher than $b_1$. Therefore the winning number cannot be higher than $b_2 = 100 - pb_1$, with $b_2 = 100 \times(1- p + p^2))$. The elimination of the numbers higher than $b_2$ results in retaining only the numbers of the interval $I_2 = [b_1, b_2]$.

*.....( the process continues)*

*Step n*: at notional time $t = n - 1$, each player knows the result of the previous step, i.e. $b_{n-1}$, $b_{n-2}$, and the interval $I_{n-1}$, thus the new border is $b_n = 100 - pb_{n-1}$, with $b_n = 100\frac{1-(-1)^n p^n}{1+p} + (-1)^n p^n 100$. For $n \to \infty$, the corresponding interval $I_n$ can be confounded with a point (by the theorem of convergent series).

Thus, in a general way, $I_i$ is an intermediate interval of (weakly) dominant strategies. When $i$ increases, the class of the dominant strategies is reduced and intervals $I_i$ are reduced towards the eductive equilibrium. Figure 3.1 illustrates the iterative process corresponding to steps 1 to $n$.

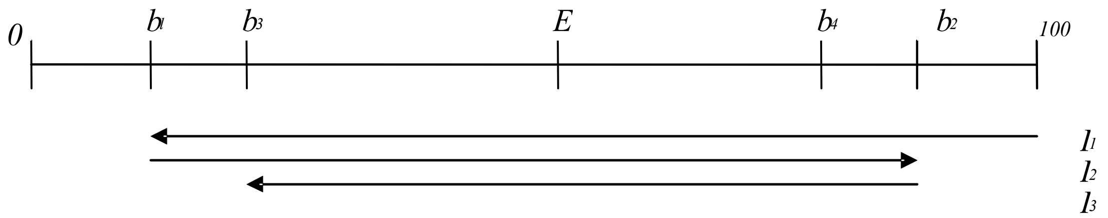


Figure 3.1. The iterative process of convergence

A unique REE, which coincides with the Nash equilibrium, is reached through eductive reasoning, at the limit: $\lim_{n\to\infty}\left[100\frac{1-(-1)^n p^n}{1+p} + (-1)^n p^n 100\right] = \frac{100}{1+p}$, with $p<1$, the stability condition. At the Nash equilibrium, each player should symmetrically choose the winning number $w$, $w = 100 - pw$, which implies $w = \frac{100}{1+p}$, which is an interior equilibrium[1].

Borders generated by eductive reasoning in the negative feedback beauty contest game are, as explained before, 100, $100 - p100$, $100 - p(100 - p100))$, …, $100\frac{1-(-1)^n p^n}{1+p} + (-1)^n p^n 100$. In Nagel's (1995) game, they are 100, $p100$, $p^2 100, \ldots p^n 100$. Both games are stable under the

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[1] With $p < 1$, $100 > \frac{100}{1+p} > \frac{100}{1+1} = \frac{100}{2} > 0$.

condition $p<1$. Successive intervals $I_0 \supseteq I_1 \supseteq I_2 \supseteq \ldots \supseteq I_n$ are reached with the same theoretical convergence speed $v_k = \frac{\|I_{k+1}\|}{\|I_k\|} = p$.[2]

### 3.3. Experimental design

Eductive reasoning is obtained through instantaneous complex introspection, as opposite to *evolutive* reasoning, based on learning possibilities offered by the repetition of the same situation. Meanwhile, the two processes have the same convergence maps (Guesnerie, 1992): the same steps are put into practice, and the only difference is the time variable, which is *notional* in the eductive reasoning and *real* in the evolutive reasoning. Therefore, in this chapter, we choose to start experimenting the negative feedback beauty contest game as a one-shot game (one period). The repeated game will be tested in Chapter 4. In the repeated game, players can observe past winning numbers and this will affect their time behaviour. In the one-shot game we eliminate the possibility for an evolutive reasoning to occur.

We conducted this experiment on 324 participants; the participants had different ages and academic background. Experimental sessions were carried out in Dijon, Agay, St.Colomban, Bucharest and Strasbourg between December 2003 and April 2004.[3]Groups had different sizes: a group of 49 participants, 2 groups of 20, 7 groups of 10, 13 groups of 8, 5 groups of 7, 2 groups of 9 and 1 group of 6. A session lasted about 10-15 minutes. According to the size of the group and the place where the experiment was conducted, sessions were computerized or not. At the beginning of the experiment, the monitor read aloud the instructions. He subsequently answered eventual questions. Participants had to choose real numbers between 0

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[2] Identical intervals :

| | |
|---|---|
| $\|I_0\| = 100$ | $\|I_0\| = 100$ |
| $\|I_1\| = p100$ | $\|I_1\| = p^0[100(1+p) - 100] = p100$ |
| $\|I_2\| = p^2 100$ | $\|I_2\| = p^1[100(1+p) - 100] = p^2 100$ |
| … | … |
| $\|I_n\| = p^n 100$ | $\|I_n\| = p^{n-1}[100(1+p) - 100] = p^n 100$ |
| *(positive feedback)* | *(negative feedback)* |

[3]In Agay and St. Colomban the participants were researchers in different fields; in Dijon and Bucharest they were high school seniors; a 49 persons group were visitors in the Open Doors Experimental Workshop in Dijon; participants in Strasbourg sessions were students in various disciplines. We thus classify our data into five groups: "visitors", "researchers", "high-school Bucarest", "high-school Dijon", "students Strasbourg".

and 100. In non-computerized sessions, participants had to indicate their choices on cards. The cards were collected after all participants had indicated their respective choice. Each card was indexed by a letter standing for group membership (if the session was conducted with several simultaneous groups) and a number standing for participant identification. The monitor calculated the target. The target was defined as 100 – ⅔× the average of all chosen numbers in a group and was announced to all participants. Participants could explain their choices on a paper sheet. The winning number was defined as the closest number to the target. With $p = ⅔$, the REE equilibrium is 60. In computerized sessions, participants in a group had to indicate their choice through a visual basic interface and when all participants finished choosing numbers, the target and the winning participant were automatically announced. Each winner received 8 euros.

### 3.4. Results and discussion

Notwithstanding the participants' heterogeneity, we cannot reject at a 5% level the hypothesis of similar choice distributions in different groups (mean-variance test). We thus aggregate all results for the analysis (for descriptive statistics, see table 3.1. below). In this section we present several results with their justification.

| *Group* | *Mean* | *S.D.* |
|---|---|---|
| Visitors | 57.81 | 17 |
| Researchers | 57.09 | 16 |
| High-school Dijon | 56.23 | 17.5 |
| High-school Bucharest | 58.92 | 13.8 |
| Students Strasbourg | 58.32 | 11.5 |
| total | 57.67 | 15.51 |

Table 3.1. Descriptive statistics for each group

***Result 1:*** **The distribution of choices presents several choice-concentrating peaks. These peaks correspond to the sequence 33, 48, 54, 60, 67, 78: these are the bounds of dominating intervals[4] for parameter *p* = ⅔.**

[4] $I_0 = [0,100]$, $I_1 = [33,100]$, $I_2 = [33,78]$, $I_3 = [48,78]$, $I_4 = [48,67]$ etc.

Figure 3.2 depicts aggregate results.

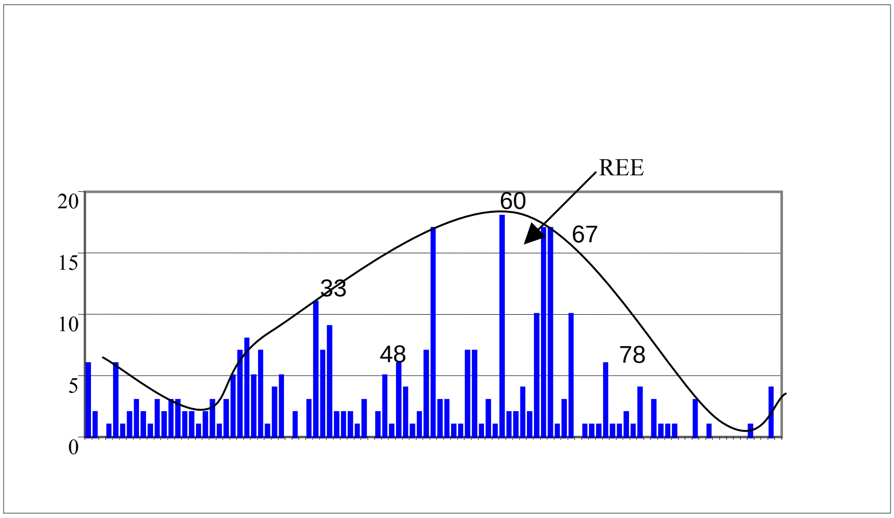


Figure 3.2. Choice frequency in the beauty contest game with negative feedback

The distribution mode is at 60 (7% of choices), which corresponds to the REE. Camerer (1998) presents only a 2.2% percentage for the REE on the positive feedback game (numbers between 0 and 100, $p = ⅔$). More than $\frac{2}{3}$ of participants choose numbers corresponding to at least one step of eductive reasoning (see Table 3.2.). 30% of participants choose low numbers, which corresponds to an absence of eductive reasoning. This percentage is comparable to the one observed in positive feedback games. Following comments by subjects, low numbers are chosen for traditional reasons: age, anchoring, university background.

| *Intervals* | *Negative feedback* | *Positive feedback (Camerer, 1998)* |
|---|---|---|
| $I_0$ | 100% | 100% |
| $I_1$ | 70% | 85% |
| $I_2$ | 64% | 62% |
| $I_3$ | 47% | 43% |
| $I_4$ | 39% | 30% |
| $I_5$ | 28% | 16% |
| $I_6$ | 14.2% | 12% |
| $I_7$ | 9.6% | 3% |
| $I_8$ | 7% | 2.2% |

Table 3.2. Distribution of choices in each interval

***Result 2:*** **The average depth of reasoning in the game with negative feedback is around two steps of eductive introspection.**

In order to explain this result, we use a variation of the cognitive hierarchy (Camerer, 2003). The cognitive hierarchy (CH) model supposes that the participants' population is split between a percentage of zero-level players (who randomly choose numbers) and a percentage of higher level players. A *k*-type player ($k \geq 1$) believes that the other players belong to a lower level (between 0 and *k*-1). The CH model is based on two types of sophistication: an *horizontal* sophistication, corresponding to different eductive steps, and allowing *k*-type players to best respond to a population of (*k*-1)- players, $\forall k \geq 0$; a *vertical* sophistication, allowing players to take into account other players' heterogeneity: we will denote these players $k'$ - players because they consider a population composed of players ranging from level 0 to level *k.* In CH, a $k'$ –type player is able to estimate the percentages of each type of 0 to (*k*-1)-players and to select a number which is a best-response to this distribution.[5] In our variant we suppose that a $k'$- player considers other agents of level 0 to *k included*. We make an horizontal myopia assumption: a $k'$ –player doesn't see a ($k'$-*i*)- player, $i \leq k$, but only *(k-i)*-players, $i \leq k$. This model allows us to estimate the number of eductive steps performed by players.
Beliefs of $k'$-type players*,* denoted $g_{k'}(h)$, on the percentages of *k*-type players, are given by the normalized distribution $g_{k'}(h) = f(h) / \sum_{l=0}^{k} f(l)$, for $h \leq k$ (Camerer and al., 2003). $k'$ - players use these beliefs to compute best-responses. Camerer and al.(2003) make the assumption that memory constraints and uncertainty about others' rationality suggest that $f(k)/f(k-1)$ is proportional to $1/k$, which implies $f(k) = e^{-\tau}\tau^{k}/k!$, the Poisson distribution, where $\tau$ is the mean and the variance of the number o seductive steps. Camerer and al. find $\tau$ between 1 and 2. With our data we estimate $\tau$ =1.4 (for a mean in choice of 57.67). Therefore the result is that in the negative feedback beauty contest game, players apply at most 2 steps of introspection, in coherent connection to the results on the positive feedback game. Meanwhile, this result suggests that players do apply the eductive reasoning, but in an imperfect way.

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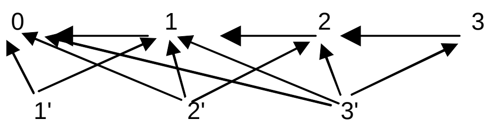
[5]Let us give the example of a population with a maximum reasoning depth 3. In CH, player 3 does not exist. Pointed agents are perceived agents.



***Result 3:*** **The empirical speed of convergence of the eductive process is higher in the negative feedback beauty contest game than in the positive feedback game.**

The speed of convergence of the iterative process $v_t$ was defined earlier and we have demonstrated that both games (with negative and positive feedback) have the same theoretical convergence speed (which equals $p$). We measure this speed by dividing the weight of an interval to the weight of the previous interval (the weight of an interval is the proportion of choices in that particular interval). Table 3.3 presents results for the first six intervals.

| | *Negative feedback* | *Positive feedback*[6] | *Positive feedback*[7] |
|---|---|---|---|
| $v_1$ | 0,7 | 0,91 | 0,85 |
| $v_2$ | 0,91 | 0,8 | 0,73 |
| $v_3$ | 0,73 | 0,56 | 0,69 |
| $v_4$ | 0,82 | 0,33 | 0,71 |
| $v_5$ | 0,74 | 0,56 | 0,54 |

Table 3.3. Speed of convergence

In all cases, this speed exceeds theoretical speed (equal to 0.66) and for all steps, except the first, speeds of convergence in the negative feedback game are significantly higher (at a 5% level, Wilcoxon) than those of the positive feedback game. According to the results of Bosch and al. (2000), the players are able to guess the REE in the positive feedback game if they are able to put into practice the first three steps of the eductive reasoning. Indeed, the speeds of convergence for the first 2 stages (over the first 3 intervals) are higher than those envisaged theoretically. Our results show that, despite of the fact that the process of eductive reasoning begins (empirically) more quickly in the game with positive feedback (at the first step 0.91>0.7), empirical speeds of convergence remain increasingly higher in the negative feedback game (for the 5$^{th}$ step, for example, 0.74>0.56). The explanation of the difference in the first period, not corresponding to the tendency, is due to the weight of the low choices (between 0 and 33): a phenomenon observed in the experiments is the choice of "small numbers". Moreover, it appears on the comments sheets, that some students confess to have

[6]Nagel (1995), data on graphic.
[7]Camerer (1998, $p$=0,7)

chosen their age; let us imagine a 21 years old student who chooses 21. If he plays the game of the beauty contest with positive feedback, this "irrational" choice could be confused with the choice of an agent having undertaken at least 2 steps of eductive reasoning (at every additional step the dominated strategies corresponding to numbers on the right side of the interval [0,100] are being eliminated). Thus the choice of small numbers in the positive feedback game increases the number of choices in the "most dominant" intervals (as in this case the most dominant intervals are also those closest to the REE, which is at 0). If the student that we took for example plays the negative feedback beauty contest game, his choice (21) is part of the dominated strategies being eliminated at the time of the first step of the eductive reasoning (small numbers are registered in dominated intervals in the negative feedback game). We will try to establish with result 4, starting from this configuration and by repeating the game, that there is a faster tendency of convergence in the negative feedback game.

***Result 4:*** **With equal depth of reasoning, numbers announced in the negative feedback game would allow reaching the REE faster than in the positive feedback game, if the two games were to be repeated with players of a static type[8].**

Let us imagine that the games (with positive and negative feedback) are being repeated starting from the initial configurations that we analyzed and that the players preserve their type all along the experiment. We will carry out simulations to test this assumption, since in a repeated experiment a player is likely to modify his "type". In the positive feedback game, with a depth of reasoning of level 2, the eductive reasoning leads the subjects to choose numbers very far away from the REE. Since in the negative feedback game the empirical speed of convergence is higher, we can make the assumption that the repetition of the game will lead the subjects to values closer to the REE in the negative feedback game than in the positive feedback game, for an equal depth of reasoning. In order to support this conjecture, we present results of simulations carried out starting from the answers observed in the experiments and from the number of steps of reasoning put into practice.

Simulations are carried out on the basis of heterogeneous group of 10 players with an average depth of reasoning of 1.4 who take part successively in 10 periods. The depth of reasoning

[8] Their type does not improve.

determines the "type" of the player. A player of type *k* preserves his type for all the game. The structure of the population for the first period is the one rising from our previous estimates. It remains constant thereafter. Thus, players of type 0 and 2 are represented at 30% and players of type 1 at 40% (in the preceding estimates, we found that our population was composed of 30% players of type 0, 41% players of type 1 and 29% players of type 2). They choose numbers according to predictions' of the model of cognitive hierarchy. Thus they answer permanently, at each new period, to the same structure of population, each one according to its type. Let us take the example of a group. At the first period, the answers of the 10 players of the group are drawn from the data pool by respecting the proportions of the various types of players. The answer of a player of type *k* in period $t \geq 2$ is contingent only with its type and the average of the previous period: the average of a period synthesizes the fixed proportions of the various players and their answers; thus, the average of the previous period constitutes, for player *k*, the starting point of the eductive reasoning of which we presented the steps at the beginning of this chapter. Compared to this starting point, the player of type *k* announces a number which corresponds to *k* steps of eductive reasoning. Thus, for example, a player of type 1 announces at the period *t* a number equal to $100 - \frac{2}{3} \times$(mean of period $t$-1).

We compare the results of 200 simulations for positive and negative feedback games, by maintaining the same population structure. We calculate the difference between a period result and the REE and present the average layout for the 10 periods. Thus the figure 3.3 shows the variations at the REE observed in the game with negative feedback and the game with positive feedback.

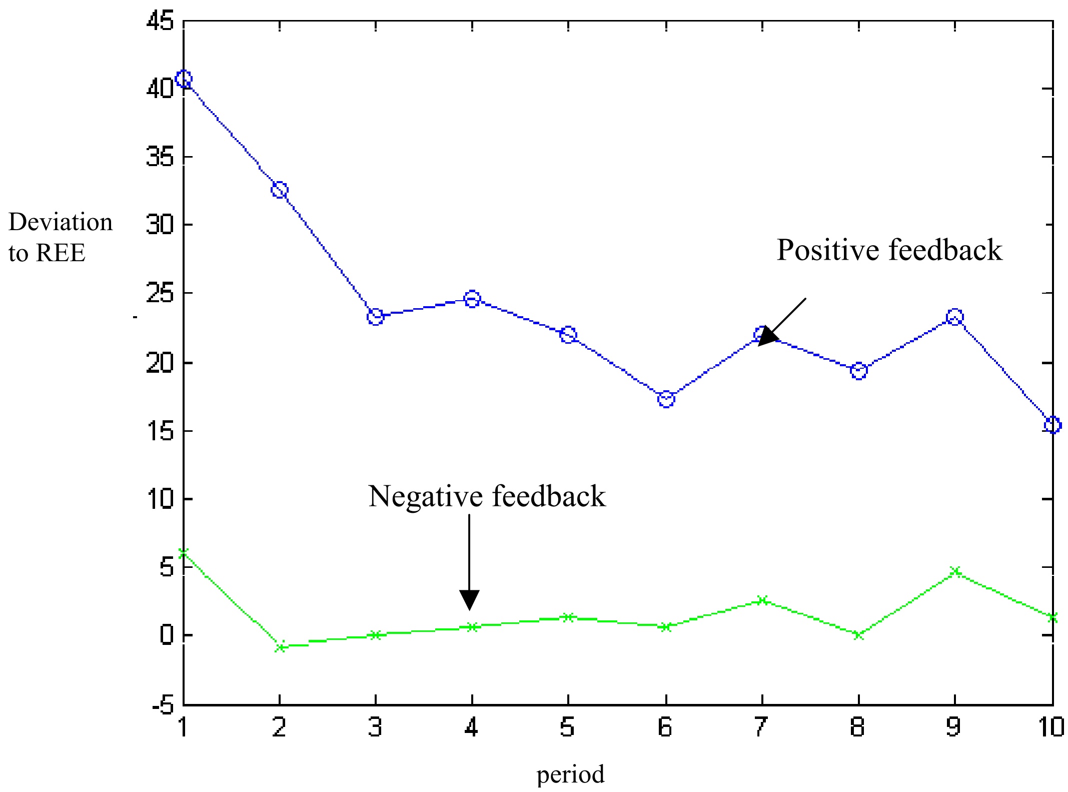



Figure 3.3.Deviations with the REE
($p$=⅔,10 periods, 10 heterogeneous players with an 1.4 average depth of reasoning)

Figure 3.3 shows that the differences between the results of the positive feedback game and the REE (0) are higher than differences between the results of the negative feedback game and the REE (60). The answers in the positive feedback game remain durably overestimated compared to the REE. The layout never goes down below 10. In the negative feedback games, the REE is reached in the second period and thereafter the oscillations around this equilibrium remain small. Since the depth of reasoning and the structure of the populations cannot explain the better results obtained for the negative feedback game compared to the positive feedback game, we conclude that this is due to the particular structure of these situations. In the negative feedback game, the iterated elimination of the dominated strategies allows a repeated "sweeping" of the REE. The REE is scanned at each crossing of an eductive reasoning step. Thus the REE operated as a point of stabilization in beliefs, since each choice strayed from the REE is counterbalanced by a result of opposite distance.

### 3.5. Conclusion

In this chapter we experimentally examined the negative feedback beauty contests games. These games reproduce in a simple way the structure of negative feedback situations such as those of corn production or financial investment. We showed that the installation of an eductive reasoning in these situations allows reaching the REE faster within equal depths of reasoning (2) compared to positive feedback situations. Estimation and simulation results reinforce the thesis according to which the negative feedback environments are stabilizing situations and confirm the theoretical results of Guesnerie (2004), according to whom the negative feedback environments dominate those with positive feedback from the installation of coordinated anticipations point of view.

**Contents**

# Chapter 4

# Why do we guess better in negative feedback situations?
# A multi-period experiment
# on beauty contest games with negative feedback

## 4.1. Introduction

Trying to observe *homo oeconomicus*' behaviour signifies questioning his existence; no need for observing homo oeconomicus should exist, as he is supposed to act following perfect rationality assumptions and therefore we can infer and know at any moment his strategies simply by deriving the fundamentals. But in the last decades, experimental and behavioural economists tried to show that the hypothesis of instantaneous (complex) inferences that a perfectly rational individual should be able to perform when choosing an action is unrealistic; thus *homo sapiens* came back to the attention and became the observation target of experimental economists. This was motivated by the need to relax two assumptions from the standard view: perfect substantive rationality and perfect collective introspection based on perfect common knowledge. Anyway, there is evidence that participants in real or experimental markets or games do reason while interacting (and reason about interactions). Therefore, the question is to which extent this activity is performed before taking an action.

Following Binmore (1987), Guesnerie (1992) and explanations in Chapter 1, assuming participants in an economic interaction to do (limited, simultaneous and collective) sophisticated reasoning allows us to investigate their eductive abilities. Since Nagel (1995), Ho and al. (1998), Camerer (2003), addressing this type of reasoning in the experimental laboratory became easy by using guessing games.

Eductive reasoning relies on the mental activity of agents who "forecast the forecast of others", by understanding the logic of the situation, i.e. they use sophisticated reasoning rules to "guess" the equilibrium. It differs from evolutive reasoning, based on the repetition of the situation and inherent to experiments where subjects are asked to take repeatedly analogous decisions. The basic idea of the eductive activity was first introduced by Keynes(1936), who stressed that there are traders who "devote [their] intelligences to anticipate what average opinion expects average opinion to be. And there are some, I believe, who practice the fourth, fifth and higher degrees". Talking about reasoning degrees or depth allows us to address the eductive reasoning issue even if this process may not be complete. Indeed, this is the empirical evidence device: people do not perform complete eductive programs when taking decisions. They stop at some point in the iterative chain of sophistication.

We presented guessing games in Chapter 2; previous experimental work only investigated positive feedback guessing games (BCG+) *à la Nagel* (called beauty contest games), that inspect the convergence of the reasoning process towards the equilibrium. As in our previous chapter, we experiment here the introduction of negative feedback in these games (BCG-). Negative feedback stabilizes the system, as explained in Chapter 1. This is possible through a modification of the convergence process to the equilibrium solution, and through the interior location of this point[1].

In the BCG+, both the eductive reasoning process and the evolutionary dynamic process, converge to the rational expectations equilibrium monotonically. For example, if the numbers are chosen between 0 and 100 with $p < 1$, the process begins with a high value and converges monotonically towards 0. In contrast, with negative feedback, the convergence to the equilibrium point is described by a non-monotonic damped oscillating function (that is, a function that approaches the equilibrium solution by oscillating up and down around the equilibrium with decreasing amplitude; dominant strategies are eliminated on both sides of the interval and not only in one direction). This process is of course only possible if there is an interior equilibrium, instead of a boundary equilibrium as in the BCG+. Interior equilibria have been investigated ealier by Camerer and al.(1988) and by Guth and al.(2002), but under

[1] Details are presented in Chapter 2.

monotonic convergence, i.e. with a positive feedback structure[2]. Thus we will refer to our variant of the beauty contest game as "beauty contest games with negative feedback and interior equilibria" or simply negative feedback beauty contest games.

We introduce in this chapter the same game as in the previous chapter, but in a repeated version. Beside exploring the issue of possible smaller deviations from the equilibrium in first round choices as a consequence of the repetition focusing and hypothetical faster convergence to equilibrium, we address in this chapter the question of a cost-benefits analysis of information processing and aim at showing that two sided elimination of strategies provides "more information" than one-sided reduction because with two-sided reduction the choice interval is "scanned" several times. Therefore it is computationally easier for subjects to localize the equilibrium solution. More generally, actions generating negative feedback lead to a more predictable outcome.

The assumption of null informational cost is unrealistic. Whenever understanding (by processing) information is costly, an agent endowed with rationality face the decision problem of whether the expected benefit of acquiring or processing the information is higher than the cost of processing. Therefore the amount of information processed by individuals becomes an element of the decision making process. When full rationality is scarce, the deliberation cost must be taken into account (Conlisk, 1996) because good decisions are costly.

This chapter is organized as follows: section 4.2 describes the theoretical structure of the game (as in the previous chapter) and the method used to treat information; section 4.3 presents the experimental design. Section 4.4 is devoted to results presentation (in this section a brief comparison with results from monotonic interior equilibrium game is done). Section 4.5 concludes.

### 4.2. Theoretical background

We first mathematically describe the game, and than introduce the mechanisms that we will use in the information cost-benefits analysis.

[2] The winning number in their design is $p \times (c + mean)$).

### 4.2.1. Description of the game

A number of players, $M$, simultaneously choose a number in the interval [0,100]. The game is played for several periods. The winner of a round is the player whose with the closest choice to the target $100 - p\bar{x}$, where $p$ is a constant ( $p < 1$), and $\bar{x}$ is the average of all chosen numbers within a period: $\bar{x} = (x_1 + x_2 + \ldots + x_M)/M$.

We describe the eductive reasoning supposed to take place in notional time, i.e. instantaneously (Guesnerie, 1992):

*Step* 1: at notional time $t = 0$, each player realizes that the average cannot exceed the value $b_0 = 100$. This results in eliminating all the numbers ranging between 0 and $100 - p\times 100$. Indeed, the value of the winning number cannot be lower than $b_1 = 100 - p\times 100$. This lower limit generates a new interval $I_1 = [b_1, b_0]$, including the weakly dominant strategies, after the elimination of the strategies lower than $b_1$.

*Step* 2: at notional time $t = 1$, each player knows the conclusion of *step* 1, and consequently that the other players will only select numbers higher than $b_1$. Therefore the winning number cannot be higher than $b_2 = 100 - pb_1$, with $b_2 = 100 \times (1 - p + p^2)$). The elimination of the numbers higher than $b_2$ results in retaining only the numbers of the interval $I_2 = [b_1, b_2]$.

*.....( the process continues)*

*Step n* : at notional time $t = n - 1$, each player knows the result of the previous step, i.e. $b_{n-1}$, $b_{n-2}$, and the interval $I_{n-1}$, thus the new border is $b_n = 100 - pb_{n-1}$, with $b_n = 100\dfrac{1-(-1)^n p^n}{1+p} + (-1)^n p^n 100$. For $n \to \infty$, the corresponding interval $I_n$ is confounded with a point (by the theorem of convergent series).

Thus, in a general way, $I_i$ is an intermediate interval of (weakly) dominant strategies. When $i$ increases, the class of the dominant strategies is reduced and intervals $I_i$ are reduced towards the eductive equilibrium. Figure 4.1 illustrates the process by which iterations are conducted, in steps.

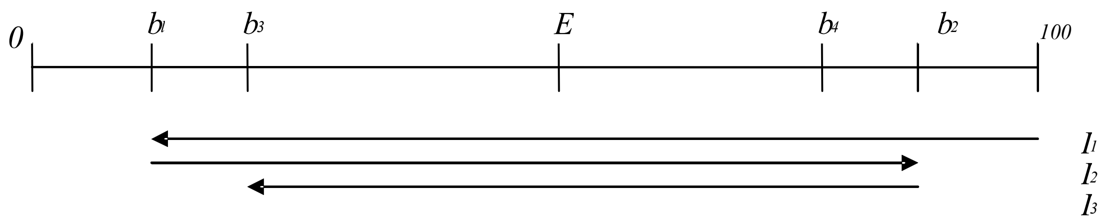



Figure 4.1. Iterations in the BCG-

A unique REE, coinciding with the Nash equilibrium, is reached trough eductive reasoning, at the limit: $\lim_{n\to\infty}\left[100\frac{1-(-1)^n p^n}{1+p}+(-1)^n p^n 100\right]=\frac{100}{1+p}$, with $p<1$, the stability condition. At the Nash equilibrium, each player should symmetrically chose the winning number $w$, $w = 100 - pw$, which implies $w = \frac{100}{1+p}$, an interior equilibrium[3].

### 4.2.2. Useful information: cost of marginal sophistication and informational benefit

Cognitive psychology has largely documented the fact that humans have limited cognitive abilities (among the last studies, Camerer(2003), Mills and Keil (2004), Todd and Gigerenzel (2003)). Even if cognitive capacities are not binding, standard economic thinking would predict that economically boundedly rational agents will balance costly thinking and the expected rewards of the thinking activity. This means in our context that the number of reasoning steps will be either bounded by the agent's cognitive ability or by his expected net reward of an additional step. We will show that if agents behave is such a manner, their strategies will convergence closer to the REE in negative feedback guessing games than in the BCG+. The reason is that the eductive process in the BCG- generates a larger amount of information in the early steps of reasoning, because the structure of those games allows players to better *localize* the REE through an exploration process over the whole strategy space. Therefore in this section we will put forth our theoretical predictions as several conjectures.

[3] With $p < 1$, $100 > \frac{100}{1+p} > \frac{100}{1+1} = \frac{100}{2} > 0$.

***Conjecture 1*: First intervals useful information is higher in the BCG- than in BCG+.**

This statement is based on the calculation of *useful information* gained in each iteration on the basis of the Shannon entropy criterion. After each step of the eductive process, each player discovers a new guessing interval containing dominant strategies: in every guessing game, the sequence of narrowing down intervals is $I_0 \supseteq I_1 \supseteq I_2 \supseteq ... \supseteq I_n$. As explained in Chapter 1, Dehaene (1993, 1997) has shown that humans perceive numbers on a mental logarithmic scale oriented from left to right: the smaller are the numbers, the more space they hold on this scale and the more they approach (by an ordinal position) the left margin (this is called the SNARC effect for Spacial-Numerical Association of Response Codes). When confronted to a number, human mind has to place it on this scale. For example, the eductive process described earlier starts at $b_0$. When switching from $I_0$ to $I_1$ (and reaching $b_1$), the brain needs to *scan* all numbers between $b_0$ and $b_1$ in order to locate the border $b_1$. When switching from $I_1$ to $I_2$ one needs to scan all numbers between $b_1$ and $b_2$ etc... We assume that the useful information depends on the exploitation of the guessing interval. Thus useful information for step $i$ is obtained by the intersection of the scanned interval (scanned numbers between $b_{i-1}$ and $b_i$) with the dominant strategy interval $I_i$ obtained by the elimination of the dominated strategies. More and more eductive steps in the negative feedback guessing game allow the subject to scan several times the REE, because it is included in all guessing intervals. In contrast, in the BCG+ game, the scanned intervals only allow to acquire information on dominated strategies and on one single point corresponding to a border. Indeed, when switching from a border to another, none (except the border point) of the dominant strategies is scanned (because in the BCG+ borders $b_i$ are monotonically ordered while in negative feedback game, they alternate). We calculate, for each game, the average available information, according to the information theory formula:

$$H(I) = \sum_{i \in I} prob_i \log_2 \left(\frac{1}{prob_i}\right)$$

where $prob_i$ is the probability of occurrence of element $i$, $I$ stands for the information and the number of possible events is $h - l$. The probability $prob_i$ of an element in the BCG- is $prob_i = \dfrac{abs(b_i - b_{i+1})}{h-l}$, because all scanned numbers are in the dominant strategies intervals, thus they are useful information. The probability $prob_i$ of an element in the BCG+ is equal to 0.01 because all scanned numbers except one correspond to dominated strategies and thus they are not useful information. Thus we calculate the available information for the BCG- as:

$$H(BCG-) = \sum_{i \in I} \frac{abs(b_i - b_{i+1})}{h-l} \log_2 [\frac{h-l}{abs(b_i - b_{i+1})}],$$

whereas *H(BCG+)* is a sum of constants. Using calculations from chapter 2, the precedent equation can be reduced to:

$$H(BCG-) = -\log_2 p \sum_{i \in I} (1+i) p^{1+i}$$

For 51 intervals with an amplitude of 0.0000002 for the last one, *H(BCGwnf*) = 3.5 and *H(BCG*) = 3.38.

***Conjecture 2*: The lower *p*, the higher the relative informative power of the first intervals in the BCG-.**

The marginal useful information measures the increase in total information that a player obtains with an additional step of eductive introspection. Under the assumption of rational behaviour, as the number of steps becomes larger, the probability of guessing the winning number increases. The marginal information curves in the BCG- can exhibit different profiles according to the value of *p*. For relatively small values of *p*, the marginal information curve is decreasing, whereas for relatively high values of *p* the curve is bumped. Figure 4.2 describes the marginal information curves for both guessing games with a high and a small value for parameter *p* (⅔ and ¼) and for $q$ = 100. The areas under the curves measure the information as calculated before. We consider in this graph informative intervals of a width that exceeds 0.05, which corresponds to intervals $I_1$ to $I_{20}$.

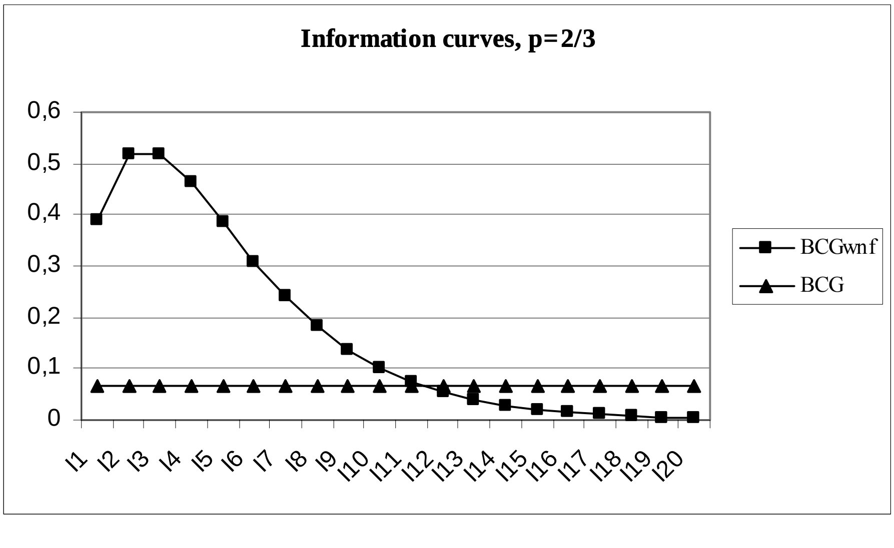



Figure 4.2.(a) Information curves for 20 narrowing down intervals in the BCG- and BCG+ (*p*=⅔)

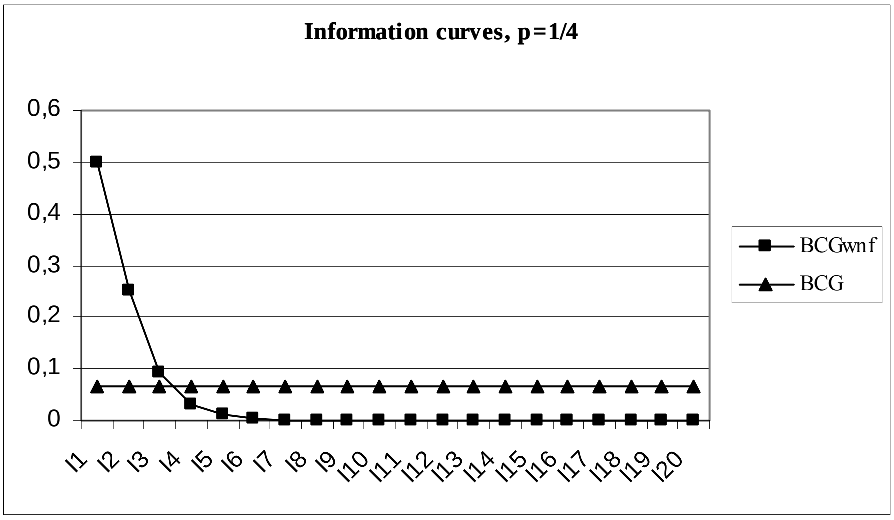



Figure 4.2. (b) Information curves for 20 narrowing down intervals in the BCG- and BCG+ ($p$=¼)

The marginal useful information, as depicted before, measures the additional benefit that an individual can obtain from one more step of eductive introspection (the marginal benefit of the sophistication effort). For a small value of $p$, the marginal benefit is rapidly decreasing; the curve stands for a fast eductive process: in such a case, discovering the very first dominance intervals is enough to "understand" where the REE is located and calculating more and more eductive steps does not add significant additional information. For a larger value of $p$, first steps are more informative because the convergence process is slower; it is therefore important to discover several intervals until one's can "jump" at the REE.

***Conjecture 3*: For any value of *p*, the initial steps of the eductive process are always more informative for locating the REE, in the BCG- than in the BCG+.**

Therefore, for a given level of precision, fewer steps are required, because the marginal information about the location of the REE becomes redundant after several steps. We thus put forth the assumption that in BCG- discovering more and more dominance intervals is not necessary (less and less informative) starting from a *specific point*. In fact, the figure shows that, for every value of $p$, first useful information intervals in the BCG- contain more informative power than first useful information intervals in the BCG-, which corresponds to good news about guessing the REE: in the BCG- the first intervals are those who inform better about the location of the REE, and discovering a high number of dominant strategies intervals is not necessary, because marginal information about the location of the REE is redundant. In the BCG+, each new interval has the same (low) informative power. At the limit, one has to discover all intervals to reach the REE. Therefore, as long as additional information is useful, *H(BCG-)* exceeds *H(BCG+)*.

***Conjecture 4*: The stopping rule in the eductive reasoning process is determined either by the cognitive constraint or by a benefit-costs analysis.**

Assume that sophisticated reasoning is costly. A rational agent will therefore stop calculating at step $k$ for which the marginal cost of reasoning equals the marginal (informational) benefit. Let us note this condition by $C_m(k) = B_m(k)$ and let $k^*$ be the (unique) solution of this programme. Assume now that the agent's cognitive capacity is bounded and let us note $m$ the maximum number of steps he can achieve. If $m < k^*$, his cognitive constraint is saturated before reaching the optimal number of steps. The number of steps of thinking, $k°$, is therefore defined by $k° = min\ (m,\ k^*)$. The solution of this system helps determining where exactly is located the *specific point* from which in the BCG- one's can jump to the REE.

According to the above arguments, agents will tend to make more steps of reasoning in the BCG- than in the BCG+ because the marginal benefit is always larger in the BCG-. There is a further reason, which can explain why subjects get closer to the REE in the BCG-, even if $k°$ (or the distribution of $k°$ in a population) is the same in both games. Bosch and al. (2000) make the assumption that once the first 3 steps of eductive reasoning have been implemented, subjects in BCG+ sessions can "jump" to the infinite step of reasoning, because, while calculating the first 3 steps, they learn the direction in which the eductive process should lead them. Our main result is related to the discovery of the $k$ first steps and their informative powers. In the first steps, players in the BCG- collect more information than in BCG+. Starting from interval $I_k$, each additional interval provides less additional information. Therefore, even if the process of convergence to the REE is likely to succeed in both games, it will be faster-started in the BCG-. This analysis let us to put forward the *hypothesis* that this *specific point* is the point at which reflective beliefs become intuitive; for small values of $p$ the rank of this point will be smaller than the rank of the corresponding point for high values of $p$.

We conclude that if the structure of an environment is one of negative feedback, the convergence to the REE is improved because the information is better exploited.

## 4.3. Experimental design

The experiments were conducted at the LEES laboratory in May 2004 and at the LEEM laboratory in October 2004 and April 2005. Participants were students from various disciplines. The software of the computerized experiment has been developed within z-Tree (Fischbacher, 1999). A total of 128 subjects participated in the experiment[4]. They were split into 16 independent groups of 8 subjects each and were matched as partners. Each session consisted of 10 rounds, and lasted about 40 minutes. Our main question is about first round choices; we assumed that a *repetition* factor is likely to work from the very first period in the following manner: subjects' choices will be affected by the fact that the situation will repeat in exactly the same conditions; a repeated situation is likely to evolve probably into the direction of a better outcome, as subjects acquire experience. We assume that subjects understand that they will become a kind of experts with the repetition of the game; as experts, their choices will be better. Therefore this will focus their attention on the construction of their strategies: I know that I will become better, so I try to become better starting from now, and in this way I am likely to be even better and especially better than my opponents.

Subjects received a written questionnaire to check their understanding before the beginning of the session and written instructions (in Appendix). They were required to choose real numbers between 0 and 100. The winner was the subject whose chosen number was closest to $100 - p \times mean$. We set $p = ⅔$ for 9 groups and $p = ¼$ for 7 groups, in order to test a small and a high value for $p$. The REE equilibrium is at 60 for the $p = ⅔$ case and at 80 for the $p = ¼$ case. Choosing these two particular values will help us to address hypothesis on the use of information presented in section 4.2. The winner of a round received a prize of 8 euros. In case of tied winning numbers, the prize was equally split between them. Thus a subject could earn a maximum of 80 euros for a session. The maximum amount earned by a subject was 32 euros. Table 4.1 gives a summary of the experimental design.

| Value of p | REE | Number of groups | Number of subjects |
|---|---|---|---|
| ⅔ | 60 | 9 | 72 |
| ¼ | 80 | 7 | 56 |

Table 4.1. Experimental design

[4] An additional group of 32 subjects participated in an experiment that we will present as a comparison device in the results section.

### 4.4. Results and discussion

The next figure presents winning numbers for all groups and for the two values of parameter $p$.

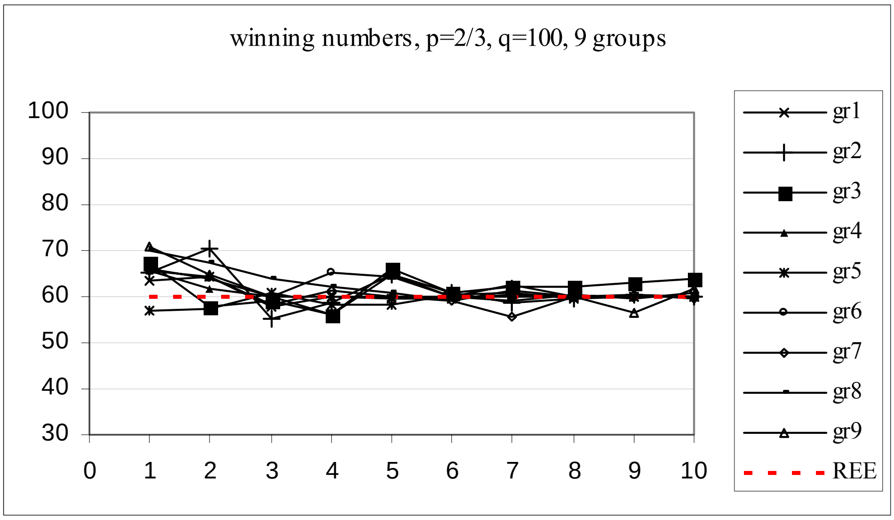



Figure 4.3. (a) Winning numbers for the BCG-, p =2/3
(groups of 8 subjects)

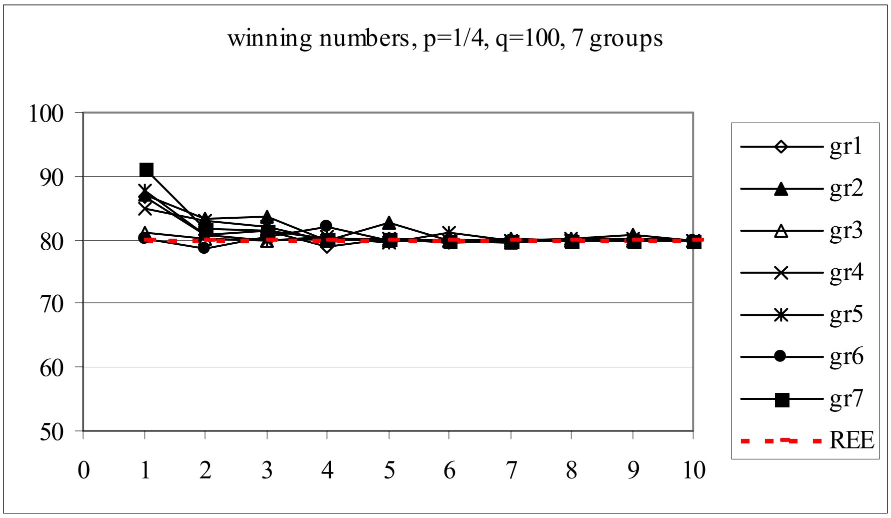



Figure 4.3. (b) Winning numbers for the BCG- , p=1/4
(groups of 8 subjects)

***Result 1:*** **First period choices correspond to the numbers assigned to steps 0, 1 and 2 of the eductive reasoning process.**

To compute this result we apply the "cognitive hierarchy" (Camerer, 2003) model. This model starts with 0-step players who randomize equally across strategies and assumes that *k*-step players ($k \geq 1$) believe all other players use only 0 to *k*-1 steps. The higher the skill of a player (high *k*), the lower he estimates the proportion of players of *k*-1. We assume that the beliefs of level *k*-players about the proportions of level h-players, $g_k(h)$, are the normalized true distribution ( $g_k(h) = f(h) / \sum_{l=0}^{k-1} f(l)$, for $h<k$). Level *k*-players choose a number which is a best response to the estimated average number chosen by the other players, computed according to their beliefs. Following Camerer (2003), we assume that more and more thinking steps are increasingly rare due to working memory constraints and doubts about rationality of others. This is captured by letting $f(k)/f(k-1)$ be proportional to $1/k$, which implies that $f(k) = e^{-\tau}\tau^k / k!$, the Poisson distribution, where $\tau$ is the mean and variance of the number of thinking steps. Camerer found that $\tau$ is between 1 and 2. That means that in the one-shot game, players do not compute more than 2 steps of thinking.

With our data we estimate $\tau = 1.55$ , for an average guess of 56.46 (for $p = ⅔$), and $\tau = 0.94$ (for an average guess of 78.04, $p = ¼$), which is consistent with Camerer's findings and is optimistic for the eductive reasoning theory in two ways: first, it shows that players do calculate at least some of the steps of iterated dominance; second, computing at most 2 steps of thinking in the first period under the negative feedback might be enough to reach equilibrium relatively fast. The values of $\tau$ that we obtained confirm our hypothesis from section 4.2. ($\tau_{⅔} > \tau_{¼}$ and $\tau_{BCG+} \approx \tau_{BCG-}$).

***Result 2*: Winning numbers exhibit oscillations around equilibrium as in the theoretical design and numbers are highly concentrated around the REE.**

For the $p = ⅔$ case, starting from period 5, more than 82% of the numbers lie in a close interval, i.e. [58.7; 61.1]; for the $p = ¼$ case, the corresponding percentage is 85% of choices in the interval [78; 81]. The smallest difference between the chosen number and the winning number becomes 0.001 in the last period.

In order to stress the importance of this result, we present for comparison the results that we obtained for one corresponding polar case ($p = ⅔$), the BCG+ with an interior equilibrium at 60. Following the experimental literature presented in Chapter 2, one of the variations on the BCG that have been experienced before was the introduction of an interior equilibrium. The rules of the game are the same (choosing real numbers between 0 and 100), but the winner is the player whose choice is the closest to *p*(*mean*+*ct*), where *p* is the convergence parameter and *ct* is a constant. We experimented this game with $p = ⅔$ and $ct = 30$. The experiments have been run in the LEEM laboratory in Montpellier in May 2004, with 32 students spilt into 4 groups of 8 partners interacting for 10 rounds. As this experiment is not in our focus, we only present here aggregate results on the convergence in figure 4.5. The process is convergent to the REE, but it remains always under the REE, even at the end of the experiment.

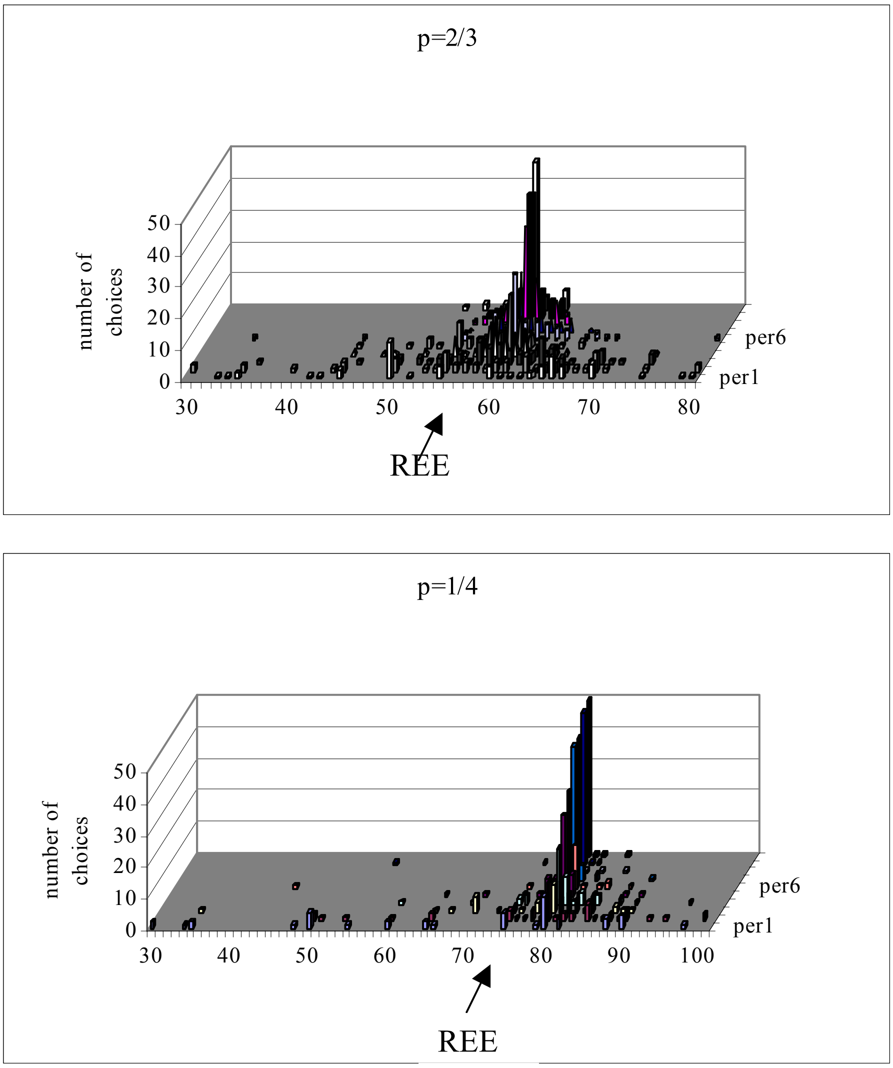



Figure 4.4. Choices for all players and all periods in the BCG-

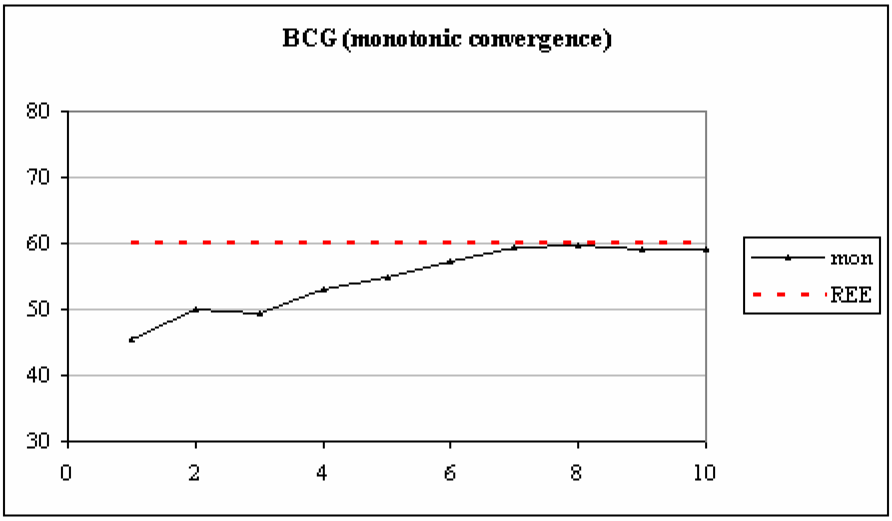



Figure 4.5. Convergence for 4 groups in the BCG+
in which the winner has to choose ⅔(mean+30)

***Result 3 :*** **With negative feedback, the "cognitive hierarchy" model predicts that a guess very close to the REE can be achieved as a winning number in the first period within only 3 steps of reasoning (for the chosen values of *p*)**

To establish result 3, we construct a simulation scheme and estimate the proportion of each type of player. We assume that players behave as indicated in the cognitive hierarchy model, i.e. they expect the others to achieve fewer iteration steps. We simulate the game using up to 4 steps of iteration. The proportions of other players are also simulated according to the rule explained in the previous section. The following table describes the simulations of these proportions in the case when a 3-step player is able to announce a number in the interval [REE-15%;REE+15%] in the first period. For example, the number in bold should be read as: proportion of 3-step thinkers according to the expectations of a 4-step thinker. We simulate environments with 1, 2, 3, and 4 types of players, corresponding respectively to 0, 1, 2 or 3 steps for the smartest player, in order to determine the value of $\tau$ which could lead to the REE±15% as the winning number in the first round. In environment *i* the "smartest" player implements *i* steps of reasoning, whereas the other players implement *i*-1, *i*-2 , …,0 number of steps. We find that an observed population of 3-level players is enough to lead a 4-level player to announce the REE.

| Type of the player→ proportion of opponents↓ | 4 | 3 | 2 |
|---|---|---|---|
| 3 | **0,31** | | |
| 2 | 0,34 | 0,50 | |
| 1 | 0,25 | 0,37 | 0,73 |
| 0 | 0,10 | 0,13 | 0,27 |

Table 4.2. Average estimated proportion of players when only 3 steps of iteration among the "observed" population are enough to announce the REE for a player who best-responds

Stating that the observed environment should be populated with players who hold beliefs of at most degree 3, in order to make it possible for an observer to announce the REE in the first period, is realistic. As argued by Sperber (1997) and explained in Chapter 1, humans have two kinds of beliefs, intuitive beliefs and reflective beliefs. From all results on the guessing game it seems that one cannot intuitively hold beliefs with $k>3$ (high order beliefs) when interaction with a situation is possible only trough a game. The 3-step order is the natural order at which reflective beliefs become intuitive because it is the level of beliefs that people hold to communicate. The winner announcing the REE should in this case implement only one additional step over the intuitive common level, which equilibrates the benefit-costs balance that we presented in the section 4.2. in a simple way.

### 4.5. Conclusion

In this chapter we presented the beauty contest game with negative feedback and interior equilibrium in a multi-period experiment. The game is still analysed from the eductive point of view and with respect to the attempt to establish a typology of players according to their depths of reasoning. Our main contribution to the understanding of this game was the formalization of the process by which the information is processed. Using the Shannon entropy criterion, we evaluated information and made a link between the Sperber analysis of reflective and intuitive beliefs and the numerical psychological research (Dehaene, 1997). Information that players take into account in their choices is denoted *useful information*. As it depends on the exploitation of the strategy interval, it will be higher in BCG- than in BCG+ in the first iterations, because strategies are numbers naturally scanned several times. As argued in Chapter 1, there is a point in the reasoning process starting from which reflective beliefs become intuitive. In order to determine where exactly is located the *specific point* from which in the BCG- one's can jump to the REE, we assumed that sophisticated reasoning is costly.

Therefore an agent stops calculating at step *k* which is obtained by the intersection between his marginal cost function and his marginal benefit (information) function, i.e. $C_m(k) = B_m(k)$, with usual notations. Anyway, there are individuals not able to reach that point, because their cognitive constraint is saturated before (they are able to compute only $k$-$s$ steps, $s<k$). There are also individuals that saturate their cognitive constraint for a value higher that *k*, but stop at step *k* because, given the structure of the population, they can win the game at a smaller cost. Therefore a guess in this game corresponds to the solution of the system composed of these two constraints. For our experiments we find a depth of reasoning smaller than 3, but which can be optimal. Results show that the *k*-step thinking with $k<3$ is "a fact of human nature" (Bosch and al., 2000) and not an arbitrary modelling restriction. Even if subjects start with a low degree of sophistication, the final winning numbers are very close to the equilibrium in the BCG-. This is possible, as showed in the traffic jam example in Chapter 1 or empirically observed by Guesnerie (1992) on the crop producers market, because situations of negative feedback are stable; therefore, "human nature" is likely to better succeed when confronted to such situations: eductive reasoning is "helped" staying in the convergence path.

# Part II

# Investigating eductive abilities:

# an approach through the cobweb markets

**Contents**

# Chapter 5

# The cobweb model

## 5.1. Introduction

In 1934, Kaldor presented a model whose graphics reminded a spider environment; because of this appearance, the model, whose interest relied in the explanation of cycles, is known as the cobweb model. It had also been theoretically addressed in the work of Cheysson (1887), Tinbergen (1930), Schultz (1930) and Ezekiel (1938), who explained it within a linear setting. Since then, it was mainly applied to markets for agricultural products such as pigs, (from whence the expression "hog cycle" derived), and corn (Hanan (1930), Ezekiel (1938) and Nerlove (1958)). The cobweb model became one of the benchmark models in economic dynamics. Freeman (1976) applied the cobweb model to job market fluctuations and Heemeijer and al. (2004) indicated a new field of application for the cobweb model, the market for computer microchips that seems to show many of its typical characteristics. Rosser (2000) gives a short overview of work on the cobweb model. Later theoretical work includes Muth (1967), Guesnerie (1992), Evans and Honkapohja (1998), Goeree and Hommes (2000) and Branch (2002).

The cobweb model is part of the family of models that assume a supply–response lag. In other words, these models characterize markets where exists an interval of time between the date when the suppliers decide how much to produce and the date when the supply actually become available on the market. Once the supply becomes available on the market, it is assumed in all these models that the market is immediately cleared: the price adjusts immediately to the existing demand.

Economic environments where supply-response lag is modelized are designed to represent markets for non-storable goods. For many commodities, particularly in agriculture, supply must be determined some months in advance. This lag is modelized as equivalent to one theoretical time period. This lag forces the suppliers (the producers) to come up with a price estimate of the next period before the actual price becomes know. So, when deciding of the amount that will be supplied to the market, suppliers have to form expectations of the future price (in turn is influenced by past prices) and base their production decisions on these expectations: since it takes one time period to produce the good, the production decision of the suppliers depends on their expectation of the price that will prevail on the market. Because of that, market is driven mainly by price predictions and resulting production decisions of the suppliers, rather than by comparable predictions and decisions of consumers.

This model is used to describe price and quantity dynamics in markets of non-storable goods. The traditional graph of a cobweb economy is characterized either by the "cobweb" cycle, either by temporal fluctuations. As the price dynamics is driven by the difference between demand and supply, the market price is constantly adapted in the direction of the excess demand. Increasing price predictions lead to increasing production, a decreasing excess demand and therefore lower prices, causing tendencies in expectations to produce a reverse effect in market prices (negative feedback).

It is important to know how expectations are formed. In this chapter we will present the analytical structure of a cobweb market and some of the theoretical issues of the price dynamics under different expectations hypothesis (5.2). Previous experimental literature will be reviewed in section 5.3 and conclusions will be given in section 5.4.

## 5.2. The theoretical approach of the cobweb market

As noticed by Van de Velden (2000), the cobweb model describes the price behaviour in a single market with one non-storable good (e.g. corn or hogs) taking one unit of time to produce. The demand, $q_t^d$, for the produced good depends upon the price of the good, $p_t$ (since the higher the price the lower the demand, the slope of the demand curve is negative). Since it takes one time period to produce the good, the production decision of the suppliers depends on their expectation of the price, $p_t^e$, that will prevail in the market, and the supply slope is positive[1]. The actual price is determined by market clearing, that is the equality of total supply and total demand. The model can thus be represented by the following equations (in which quantities are written as a function of price):

$$q_t^d = D(p_t) \quad \text{(demand)}$$

$$q_t^s = S(p_t^e) \quad \text{(supply)}$$

$$q_t^d = q_t^s \quad \text{(market clearing condition)}$$

(the subscript *t* denotes the time period).

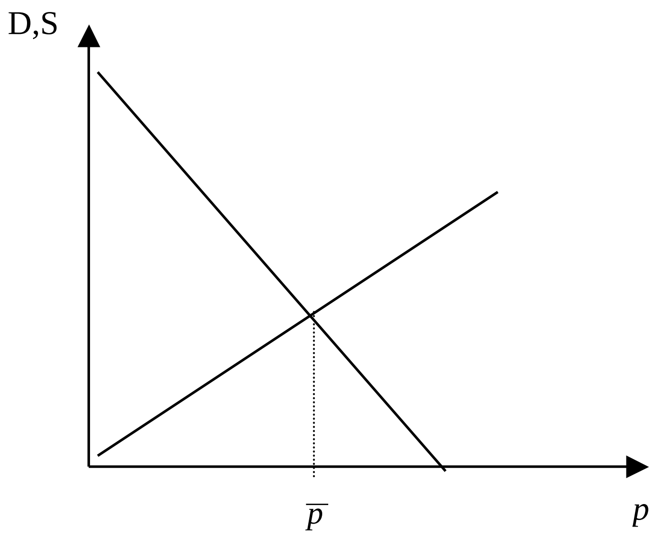



Figure 5.1.The linear cobweb model

We will deal with linear functions, so the basic equations will be:

$$D(p_t) = A - B\,p_t$$

$$S(p_t^e) = C\,p_t^e + D$$

[1] Notice that $p_t^e \equiv E_{t-1}p_t$

with $A, B, C, D$ parameters. As we imposed for the supply function to be positively sloped, $C > 0$, and for the demand function to be negatively sloped, $B > 0$.

At the equilibrium, $D(p_t) = S(p_t^e)$, i.e.

$$A - B\,p_t = C\,p_t^e + D$$

$$p_t = -\frac{C}{B}\,p_t^e + \frac{A-D}{B}$$

In the last equation, it is theoretically stated that producers' expectations and the prediction of the model have the opposite sign, a relation whose implications we will intensively use in our experimental studies.

In other terms, equilibrium will occur when:

$$p_t = D^{-1}(S(p_t^e)),$$

i.e. $p_t = p_t^e = \overline{p}$ and there is no further change in expected price. Thus the equilibrium price satisfies the condition:

$$A - B\,\overline{p} = C\,\overline{p} + D\,,$$

which gives us the value $\overline{p} = \dfrac{A-D}{B+C}$, and the equilibrium quantity supplied becomes $\dfrac{AC+BD}{B+C}$.

In Part II we will use, for the supply and demand functions, the specifications described in the following paragraph.

Let the marginal cost of each producer be given by:

$$MC(q) = \frac{q}{c} + d.$$

where $q$ is the individual quantity, $c$ and $d$ are parameters. Thus the total cost function is given by the quadratic form:

$$C(q) = \frac{q^2}{2c} + dq.$$

We assume that there is a finite number $N$ of identical producers on the market. Furthermore we assume that producers are "small" with respect to the size of the market. Aggregate supply is thus derived from producers' expected profit maximization with a monotonically increasing and convex curve and is given by:

$$S(p) = C(\,p - d\,) = Cp + D,$$

with $C = Nc$ and $D = - Cd$ ($p$ stands either for the price and for the price forecast). Assume that aggregate demand is a linear function:

$$D(p) = A - Bp, \text{ if } A - Bp > 0, \text{ and 0 if not,}$$

with $A, B > 0$ (this function can be derived from consumers' utility maximization). There is and unique equilibrium price $\bar{p}$, where aggregate supply and demand intersect. It reflects rational individual behaviour, that is, demand is consistent with consumers maximizing their utility under a budget constraint and supply is consistent with producers maximizing their profits given their price expectations. Thus the Rational Expectation Equilibrium $\bar{p}$ (REE) is reached when the price $p$ is equal to the marginal cost.

The timing of decisions is the following: at time $t$, producers decide on the production level; at time $t+1$ they sell their production on the competitive market. All the objective characteristics of the situation (cost function, demand curve, and individual payoffs) are presumed to be public information, i.e. we assume that these elements are common knowledge.

### 5.2.1. Expectation formation in the cobweb model

Several models of expectation formation have been proposed to explain forecasting activity in a cobweb market. We will describe here some of them, which are in our interest because their simplicity or of their relevance in explaining data.

#### Naïve expectations

Naïve price expectations mean that producers expect today's price to be equal to yesterday price, that is:

$$p_t^e = p_{t-1}$$

As pointed out by Ezechiel (1938), Schultz (1930), Tinbergen (1930) and Carlson (1967), the expectation function assumed in the cobweb theorem is:

$$p_t^e = p_{t-1}$$

This assumption is usually designated as the central point of the "cobweb theorem".

We replace it in the first equations:

$$B\,p_t + C\,p_{t-1} = A - D.$$

We divide by *(B+C)*:

$$\frac{Bp_t + Cp_{t-1}}{B+C} = \overline{p}$$

$$B\,p_t + C\,p_{t-1} = \overline{p}\,(B+C)$$

$$p_t = \overline{p} - \frac{C}{B}\,(p_{t-1} - \overline{p})$$

$$p_1 = \overline{p} - \frac{C}{B}\,(p_0 - \overline{p})$$

$$p_2 = \overline{p} - \frac{C}{B}(p_1 - \overline{p}) = \overline{p} - \frac{C}{B}\left[\overline{p} - \frac{C}{B}(p_0 - \overline{p}) - \overline{p}\right]$$

$$p_2 = \overline{p} - \left(-\frac{C}{B}\right)^2 (p_0 - \overline{p})$$

…

$$p_t = \overline{p} - \left[-\left(\frac{C}{B}\right)\right]^t (p_0 - \overline{p}).$$

If $-1 < \frac{C}{B} < 1$, then the price converge to its equilibrium value and the market is said to be stable. If $\frac{C}{B} > 1$ or $\frac{C}{B} < -1$, the fluctuations around equilibrium become larger and larger and the market is said to be unstable.

The stability case corresponds to the situation of a demand curve steeper than the supply curve (in absolute value), i.e., $S'(\overline{p}) < D'(\overline{p})$, equivalent to $C < B$ or $\frac{1}{C} > \frac{1}{B}$, $\frac{C}{B} < 1$.

**Adaptive expectations**

Nerlove (1958) introduced an alternative model assuming that suppliers might only gradually change their expectation about price. He postulated that expected price is adjusted according to a function of how wrong the expected price was in last period. Today's expected price is obtained by adapting yesterday's expected price in the direction of the latest observed price by a constant factor, or equivalently that the expected price for today is a weighted average of yesterday's expected price and yesterday's price (the respective weights sum to one). This can be written, indifferently,

$$p_t^e = (1-\beta)\; p_{t-1}^e + \beta\, p_{t-1}$$

or

$$p_t^e - p_{t-1}^e = \beta\,(p_{t-1} - p_{t-1}^e)$$

with $0 \leq \beta \leq 1$.

Nerlove (1958) called $\beta$ the adaptive coefficient of expectation. In order to find the stability condition in this case, Carlson (1967) provided a geometric discussion of this model and discovered the relation:

$$\frac{C}{B} < \frac{2}{\beta} - 1$$

If $\beta = 1$, then $p_t^e = p_{t-1}$ and this condition reduces to the same condition as in the case of naïve expectations. As $\beta$ gets smaller, the range of relative slopes of the supply and demand curve that will produce stability is increased. So this stability condition is less stringent than the stability condition under naïve expectations. Adaptive expectation thus has a locally stabilizing effect on the price dynamics, as compared to naïve expectations. Recently, Chiarella (1988), Hommes (1994) and Van Velden (2001) investigated the global dynamics of the cobweb model with adaptive expectations and used bifurcation diagrams to illustrate it. They demonstrate that the introduction of adaptive expectations into the cobweb model has a stabilizing effect; it dampens the amplitude of the price oscillations.

**An extrapolative approach**

Goodwin (1947) assumed that all producers expect price to change by some constant factor times the most recent change in price. Analytically, he's expectation hypothesis is:

$$p_t^e - p_{t-1} = -\rho\,(p_{t-1} - p_{t-2})$$

where $-\rho$ denotes the constant factor designed by Metzler (1941) as the "coefficient of expectation" and by Muth (1967) as the "extrapolative coefficient of expectation".

With the assumed sequence of events in this model, prices in periods $t$-1 and $t$-2 determine the expected price $p_t^e$, which in turn determines a quantity supplied; once the quantity is given, the demand function determines $p_t$. Thus, as $p_{t-1}$ and $p_{t-2}$ determine $p_t$, the time path for price can be characterized by a second-order difference equation. The conditions for stability are:

$$\frac{C}{B} < \frac{1}{\rho} \text{ for } \rho \geq \frac{1}{3}$$

$$\frac{C}{B} < \frac{1}{-2\rho+1} \text{ for } \rho < \frac{1}{3}.$$

**Rational expectations**

It is common practice under the hypothesis of rational expectations to assume that agents know the underlying market equations and collect further information only if the expected benefit exceeds searching costs. Rational expectations means that producers' subjective expected price equals the objective mathematical conditional expectation, i.e.,

$$p_t^e = E_{t-1} p_t \,,$$

where the timing $E_{t-1}$ reflects the fact that the prices have to be predicted one period ahead. When all producers have rational expectations, market equilibrium becomes:

$$A - B\, p_t = S(E_{t-1} p_t),$$

where S is the supply curve. If we consider the parameters fixed over time, it implies a linear demand curve fixed over time. Van de Velden (2001) suggests taking conditional expectation $E_{t-1}$ on both sides of the previous equation, yielding to:

$$A - B\, E_{t-1}\, p_t = S(E_{t-1} p_t).$$

Hence, the rational expectation prediction, $E_{t-1}\, p_t$, is simply the price $\overline{p}$ corresponding to the intersection point of the demand and supply curves. The RE forecast is thus given by:

$$p_t^e = E_{t-1} p_t = \overline{p}\,.$$

Given that all producers have rational expectations with forecast $p_t^e = \overline{p}$ the realized equilibrium price becomes:

$$p_t = \overline{p}\,.$$

Rational expectations are thus self-fulfilling. It follows that the true conditional expectation $E_{t-1} = \overline{p}$ coincides exactly with producers' expected price.

Guesnerie (1992) defines the concept of a rationalizable solution in the cobweb market. For that, he views the producers' problem as a normal-form game. The strategies of the producers are the sizes of their crops; hence the strategy set of a farmer is the set of positive numbers, denoted $S_f$.[2]The total crop is the sum of the profiles of production decisions and the equilibrium price is determined by the inverse of the demand function applied to this quantity.

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[2] In our experiments however we will limit the individual production possibilities to a large interval, whose upper bound will be set as the capacity of the market.

The payoff of farmer *f* is then a function of the decisions of the others (through the aggregate produced quantity) and of his own decision, i.e. the difference between the amount obtained from the selling of the production at price *p* and the total cost.

Given a strategy profile of others, the best response of farmer *f* is the maximand of this payoff. Rationalizability is derived from the hypothesis of rationality and common knowledge of rationality. The implications of these hypotheses can be exhausted through the following sequence of considerations:

*i)* Each producer is rational: agent *f* only uses strategies that are best responses to some possible profile of strategies that can actually be played by the others. Hence, rationality implies that strategies in $S_f$ that are not best responses will never be played.

*ii)* Each producer knows that all other producers are rational. Then each producer knows the conclusion of statement *(i)*, that the other producers never use a (possibly) non empty set of their initial strategy sets. Taking that into account, producer *f* may discover that some of these (remaining) strategies are no longer best responses. He will then eliminate them.

*iii)* Each producer knows that all producers know that all producers are rational.

…

*p)* Each producer knows that all producers know that all producers know …that all producers are rational.

The set of rationalizable strategies is, by definition, following Guesnerie (1992) and Pearce (1984), the intersection of all best-response strategy-sets. A rationalizable-expectation equilibrium is subsequently defined as a (measurable) function of producers' supplies, where each individual strategy is rationalizable. It consists of a probability distribution on the price generated by the market-clearing equation at time $t$+1 when it is believed by all agents at time $t$. As there is no noise in the market-clearing equations, the market-clearing price cannot be random. The rational-expectations equilibrium is then a perfect-foresight equilibrium; it follows that it coincides with the standard concept of the competitive equilibrium, determined by $S(\bar{p}) = D(\bar{p})$, is unique, and is the Nash equilibrium.

**Bounded rationality**

The unique REE could be educed in the cobweb model only under the assumption of perfect knowledge and understanding about the market equations. Knowledge and understanding are common, and individuals are endowed with high computation abilities. Therefore, they all make the introspection effort and reach the equilibrium. Several authors, like Van de Velden (2001), pointed the problem that in real markets this assumption seems to be highly unrealistic and put into practice experiments with a limited amount of information delivered to the participants. This remark captured the attention since long in the economic literature (Sargent (1993, 1999), and Evans and Honkapohja (2001) give overviews on this topic) and has been the starting point of the work on bounded rationality. Most of the recent work on forecasts formation within a cobweb model focuses more on participants behaving like econometricians rather than eductors. Authors introduce different forms of bounded rationality mainly oriented around the use of time series observations: in Sargent (1993), Evans and Honkapohja (2001), Bray and Savin (1986), Arifovic (1994), Hommes and Sorger (1998), data processing can be the use of an adaptive rule, a revision or a sample autocorrelation learning rule, a genetic algorithm rule etc. All these rules show that the REE can be achieved in a stabilizing framework (a negative feedback situation) as the cobweb market, in the long (real) run, as opposed to the eductive process presented in Part I, developed in notional time, i.e. short (real) run. The process of convergence towards the REE is achieved in steps; the same sequence of steps as in the eductive process will be reached. The main difference lies in the fact that, reported to real time, in the eductive process all steps operate at one remove, while in adaptive processes each step corresponds to a new time period.

### 5.2.2. Eductive reasoning in the cobweb model

The competitive equilibrium can be obtained either from a Walrasian tâtonnement undertaken at time $t$ with all economic actors being present or from the computation of a perfectly informed central planning board. It insures a full coordination of plans of economic agents.

At the other extreme, the concept of a rationalizable-expectation equilibrium attempts to describe some kind of minimal coordination which can take place in the absence of any explicit coordinating institution. Producers have to be envisioned as being isolated and deciding simultaneously about the size of their crops. We assume that a powerful mental process associated with the common knowledge of rationality can be set into action; that it goes beyond standard individual rationality and reflects a form of strong collective rationality.

At the beginning of each period producers choose their output level and at the end of the period all units produced must be sold at the prevailing market price. The equilibrium price can be reached through eductive reasoning if the condition $B > C$ is met, i.e. the slope of the demand function exceeds (in absolute value) than the slope of the supply function. The price adjustment process towards the equilibrium price $\overline{p}$ underlying eductive reasoning is illustrated in figure 5.2. Let us describe the eductive learning process for our specification of the cobweb model.

*i)* *Step 1*: At notional time $t = 0$, each producer knows that the maximum possible market price is $p_o = \frac{A}{B}$. For larger prices, the aggregate demand is null. Therefore aggregate supply cannot exceed $q_o$ in order to be sold at a strictly positive price. This leads to the "elimination" of any aggregate production level larger than $q_o$.

*ii)* *Step 2*: at the maximum aggregate output level $q_o$, since all production is sold on the market, it is common knowledge that the minimum selling price is equal to $p_1 = \frac{A-D}{B} - \frac{C}{B} p_0$. If the selling price is at least equal to $p_1$ aggregate supply is at least $q_1$. Therefore any aggregate output level below $q_1$ can be eliminated .

*iii)* *Step 3*: If total output were to be equal to $q_1$, it would be common knowledge that it would be sold at a price $p_2 = \frac{A-D}{B}\left[1 - \frac{C}{B} + \left(\frac{C}{B}\right)^2 p_0\right]$. But at that price level producers would like to supply an aggregate output level not larger than $q_2$. Therefore any output level above $q_2$ can be eliminated.

*iv)* *Step 4*: output levels below $q_3$ are eliminated

…………

The process of iterative elimination of aggregate output levels narrows down the set of possible output levels until the equilibrium price $\overline{p}$ is reached:

$$p_n = \frac{A-D}{B} \times \frac{1-(-1)^n \left(\frac{C}{B}\right)^n}{1+\frac{C}{B}} + \frac{A-D}{B} \times (-1)^n \left(\frac{C}{B}\right)^n p_o$$

$$\lim_{n\to\infty} p_n = \frac{A-D}{B+C} = \overline{p} \;\; (\text{ when } B>C)$$

At price $\overline{p}$ only one output level is possible, and since all producers are identical, they all produce the same fraction of total output.

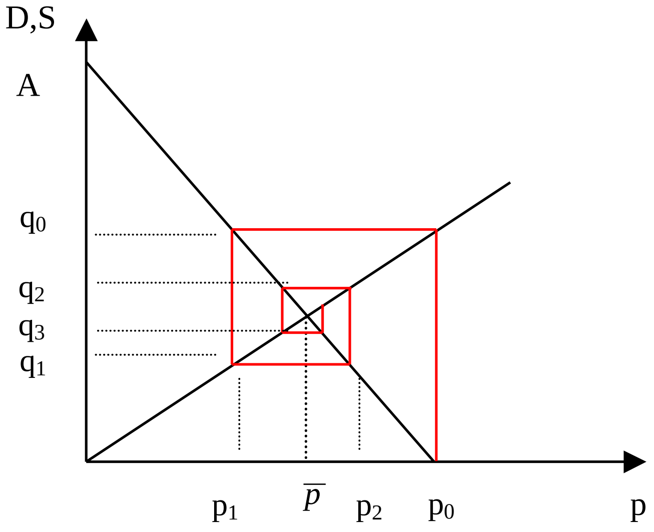



Figure 5.2.Convergence in the cobweb model
when the slope of the demand function is larger than the slope of the supply function (B>C)

A direct test of the eductive reasoning hypothesis on the cobweb market seems out of reach, since the underlying iterative elimination process is conducted in notional time. Our aim is therefore less ambitious since we only try to test the predictions of the eductive reasoning hypothesis on the basis of a simple cobweb market experiment. In particular, we are interested in the prediction that agents are able to coordinate their beliefs on a common price expectation. Experimental observations in the "guessing game" (Nagel,1995), whose beliefs structure is isomorphic to the cobweb model, seem to show that experimental subjects are able to coordinate only partly on a common expectation. Furthermore, the "depth" of eductive reasoning seems to seldom exceed degree 2.

### 5.2.3. Negative feedback in the cobweb model and equivalence with the beauty contest game with negative feedback

Let us remind the specification that we retained for the cobweb model:

$$S(p_t^e) = C\ p_t^e + D,$$

$$D(p) = A - B\,p$$

At the equilibrium:

$$C\ p_t^e + D = A - B\,p.$$

It follows that:

$$p = \frac{A-D}{B} - \frac{C}{B} p_t^e$$

As agents are supposed to be identical, we can make the following notations: $p_t^e = mean$ (the mean price forecast), $\frac{A-D}{B} = m$, $\frac{C}{B} = r$, $m$ et $r$ are here positive parameters. It implies that the price $p$ can be seen as target or as a winning number $w$ and the formula determining the price is:

$$w = m - r\ mean,$$

the general form of the guessing game with negative feedback, as stated in Part I.

As stated earlier, the negative feedback in the cobweb model is expressed through the relation:

$$p_t = - \frac{C}{B}\ p_t^e + \frac{A-D}{B},$$

where it is theoretically stated that producers' expectations and the prediction of the model have the opposite sign.

### 5.2.4. Theoretical research: conclusion

In this first part of the chapter we reviewed the formalization of the linear cobweb model with homogeneous agents. The linear cobweb model is the simplest model for a market of perishable goods in which the production decision has to be taken one period before the market clears. This is also the simplest illustration of a market with negative feedback in the sense that (first order) individual price expectations and market price realization have opposite signs. In this model, a unique equilibrium can either be reached by past data observation or by eduction. Under particular values of the parameters, this system is stable independently of the expectation rule used to describe its dynamics. According to the type of rule assumed to drive the expectation formation, the convergence process takes place in real or in notional time. When the convergence operates at one remove, this is the consequence of a complex collective introspective reasoning, called *eduction*, where individuals *forecast the forecast of the others* in steps. If they possess the ability to put into practice this reasoning ad infinitum, they act according to the REH described by Muth (1961). If they are likely to put into practice only a finite number of steps of eductive reasoning, they *i)* partially understand the REH assumptions because their cognitive constraint is binding or *ii)* they estimate that their opponents will only put into practice a finite number of steps of eductive reasoning (based on this estimation, they impose their own limits). A conceptual distinction can be made between the first case (*i*) and the second (*ii*), by saying that their rationality is limited (taken as given) or finite (self-imposed). When the convergence operates in sequential steps visible at each round or period, individuals observe past data and revise their beliefs accordingly. The process of expectations formation cannot be simply described by simple mechanical forecasting rules because individuals are likely to take into account not only past observations of the market variables, but also to learn from their mistakes.

The linear cobweb market has the same internal structure as a negative feedback beauty contest game. As negative feedback operates in a cobweb model, the market is stabilized. In our experiments in chapters 6, 7 and 8, we will try to address the question of the *type* of reasoning that participants are likely to use in a cobweb market and to *which extent*.

## 5.3. Empirical research on the cobweb market: a short review of the literature on experiments in the cobweb model

In this section we will review several studies related to the experimentation of cobweb economies. This experimental work will serve as a basis for our experiments. Nevertheless, several exploratory studies, as those of Welford (1989), or those of Hens and Vogt (2000) (in which results are not analysed), will not be reviewed.

### 5.3.1. Carlson (1967)

Carlson (1967) was the first to experimentally test a cobweb market. The motivations behind his paper were related to a series of questions constructed around the theoretical conditions leading to stability in markets characterized by a supply response lag:

*i)* *What would happen in an actual market if the preconditions for instability were met?*

ii) *Would prices go through increasingly large fluctuations, or might the early manifestation of instability lead to a change in expectation and, hence, alter or negate the preconditions themselves?*

iii) *If subjects were put into a simulated market, could existent theoretical models be used to explain the prices and quantities observed over a sequence of periods?*

In each session, every subject was given information about the cost of supplying different quantities of some fictitious commodity. Subjects were split into two groups of 20 and two groups of 25 persons and were asked to decide repeatedly (for 6 or 9 periods) on a quantity to supply before the selling price was known. Marginal cost was an increasing linear function of quantity supplied. Thus, the supply curve would have an upward-sloping straight line, if subjects always chose a quantity at which marginal cost equalled expected price. He used a step supply function that can be approximated by the formula:

$$p_t^e = 0.01 + 0.0008\, S_t$$

The actual price was determined by the total quantity supplied into a group, the price adjusting so as to clear the market in accordance with a demand function *not revealed* to the participants. For two groups the demand curve was mad flatter than the supply curve and, for the others two groups, steeper, i.e.:

$$p_t = 0.31 - 0.0007\, D_t$$

$$p_t = 0.45 - 0.0014\, D_t$$

By the cobweb theorem, one market should have been stable and experience gradual convergence and the other unstable and experience potential instability. One group of each was provided with a profit table in addition to cost information.

At every period each subject had to record on a form his estimate of what the price was going to be, his quantity decision, and the corresponding cost. They were told that the actual price depended upon the total production by all producers, i.e. the higher the total production the lower the price and inversely. Each period was closed by the announcement of the price and by the calculation of individual profits.

Results analysis focused on the verification of the theoretical assumptions about the way that price expectations are formed, i.e. testing Hooton's (1950), Nerlove's (1958) and Goodwin's (1947) hypotheses on respectively induced-caution, adaptive and extrapolative hypothesis. The main results that the author obtained are the following:

- i) *Despite different demand curves production decisions are very similar. There is no overwhelming tendency to underproduce, but ceteris paribus the greater the past fluctuations in price, the lower the quantity supplied.*
- ii) *The suppliers in the potentially explosive market seemed to be closing in on an equilibrium faster than those in the market which ought to converge to equilibrium by the stability condition of the cobweb theorem. Contrary to the cobweb theorem, both markets converged fairly rapidly: the behaviour stressed by the cobweb theorem does not materialize.*
- iii) *Estimations of parameters based on those data didn't allow to reject any of the three hypotheses about the expectation formation: adaptive or extrapolative coefficients themselves adapt to the market situation, providing one theoretical reason for expecting rapid convergence no matter what the relative slopes of demand and supply curves.*
- iv) *The results provide some support for the rational expectations hypothesis within a sample and unchanging market structure. In particular the degree of rationality of a group as a whole is particularly high in terms of average of the stated expectations.*

### 5.3.2. Burns and al. (1989), Fisher (1992)

**Burns *and al*. (1989)** have run experiments using three commodities with a supply response lag for each commodity. His main question was: *will these markets turn out to be more or less stable than the markets for a single commodity?*

Their set of experiments used the same basic design adapted to suit markets of between 5 and 22 participants. The participants could each produce in aggregate six units of output in each period, divided (by using integers only) between the three commodities. Participants made production decisions independently in advance, than the price for each commodity was determined through different and linear demand curves for each commodity. For simplicity costs were assumed to be zero. Each session was split into three parts of five periods each. In the first part, at the end of each period, participants were only told the realized price; in the second part, they were told both the prices and the aggregate quantities; in the last part they were told prices, aggregate quantities and the three demand function being used.

Their main result consists of *almost as much fluctuation in prices at the end of the experiment as at the beginning*, contradicting Carlson's result for a single commodity. He emphasized that the result lays in the difference between the explicit supply curve in Carlson's experiment and the supply curves in the current experiment (stopping at a quantity between 0 and 6).

The research of **Fisher (1992)** was firstly motivated by the necessity to explain the results obtained by Burns *and al*. and *his work had mainly looked at the stability of equilibrium and had not focused on expectation formation*. He conducted three types of experiments.

In the first type of experiments the market consisted of a single commodity and took place in three parts, performed with the same participants (characterized by the same cost function along the experiment), differing by the relative slope of the demand curve. The three (step) demand function were $p = 510 - 10\ Q$, $p = 1224 - 24\ Q$ and $p = 290 - 2\ Q$, and the corresponding total cost function was $TC = 75\ q + 25\ q^2$, $Q$ denoting the aggregate production and $q$ the individual production ($q$ could take integer values between 0 and 5). Fisher's main results on this type of experiments are:

*i)* *The equilibrium was approached quickly for each type of demand curve, but deviations were greater the steeper the curve.*

*ii)* *The average amount produced over all periods was below the competitive equilibrium, and the steeper the curve, the greater the deviations.*

In the second type of experiments, markets were constructed on the basis of the former demand and cost functions. Participants were asked to take production decisions for the first two types of the former markets simultaneously, after getting used to the third former market for several periods. At the last part of the experiment the individual production was constrained. The results suggest that:

*i)* *Equilibrium was approached quickly when the constraint on total production was not binding.*

*ii)* *There was slight underproduction on average in the steep demand function market and no clear tendency in the medium demand function market.*

*iii)* *When the total production was constrained the market was less stable than in the part where the total production was not constrained.*

In the third type of experiments, the same markets were put into practice with increased production possibilities in order to move the equilibrium position from the inelastic part of the demand curve into its elastic part. The difference between the parts of the experiment consisted in different (equally sloped) total cost functions. The main result reports *quickly convergence and no tendency for underproduction, but some increased instability*.

### 5.3.3. Hommes, Tuinstra, Sonnemans, Van de Velden, Heemeijer

The experimental research conducted at the CENDEF between 1999 and 2004 can be synthesized into 4 major papers and a PhD thesis. This is the most consequent and recent work on expectation formation in the cobweb model.

**Sonnemans *and al*. (1999)** conducted an experiment on expectation formation by the way of eliciting strategies. Their main questions were:

- *i)* *What strategies do agents use when forming expectations about future prices, and how often does the combination of these strategies lead to stable or unstable conditions?*
- *ii)* *How does learning affect the strategies and the price dynamics in the consecutive rounds?*
- *iii)* *Can market stability be attributed to characteristics of individual strategies or to heterogeneity?*

In order to answer this question they performed a four round strategy experiment in a cobweb economy: experienced subjects are asked to formulate a complete strategy (each period lasts for one week, thus the hole experiment lasted for more than six weeks), that is, a description of all their forecasts in all possible states of the world. In each period all strategies that participate in the market forecast the next price. The realized market equilibrium price is then determined by a fixed, but unknown, (linear) demand curve, and (nonlinear) supply, depending upon individual expected market prices, aggregate over all producers, i.e. the realized market price depends on all individual strategies. Reported strategies are programmed and simulated and subjects receive feedback about the relative performance on their strategy and the outcomes of five randomly selected simulations in which their strategy is included. The price $P_i$ of subject *i* determines the supply of that subject as follows:

$$S(P_i) = \frac{35 + 35\tanh(0.25(P_i - C))}{6},$$

where $C$ is the parameter determining the inflection point of the nonlinear S-shaped supply curve and is chosen randomly in each market from an uniform distribution over the interval [50; 80](which allows to the steady state to remain qualitatively the same in all markets) . The demand curve is given by:

$$D(P) = 20 - P + C .$$

The main results that they obtained can be summarized as follows:

i) *Half of the strategies do not include previous predictions; approximately half of the strategies use a weighted average of previous prices somewhere in the strategy; strategies have a tendency to become more complicated during the experiment; but all wining strategies tend to be relatively simple.*

ii) *There is clear evidence of learning between rounds but there is also clear evidence of the existence of chaos in the long run dynamics: the forecasting errors decrease significantly over the rounds, and price converge to some neighbourhood of the RE steady state, while at the same time the price fluctuations become more complicated and the fraction of chaotic price sequences increases.*

iii) *Heterogeneous markets perform better than homogenous markets, but the main source of instability is not to be found in individual strategies, but in the interaction of different strategies.*

**Hommes *and al*. (1999, 2003)**

Hommes *and al*. performed a series of experiments reported in 1999 and 2003 The experiments' aim was to test the expectations hypothesis and in general the possibility of excess volatility in the simplest dynamic economic model, the cobweb. They address several important questions:

i) *Are subjects on average able to learn the unique RE steady state price and are they better in the multi-agent treatment?*

ii) *Is there evidence of excess price volatility?*

iii) *Is there still a forecastable structure in realized markets prices if prices do not converge to RE?*

Market equilibrium equations are controlled but unknown to subjects. Subjects are asked to predict prices and their earnings were inversely related to their quadratic forecasting errors. Price realizations only depend upon subjects' price expectations. They distinguish between a single-agent treatment and a multi-agent treatment, a noise treatment (where a small normally distributed noise is added to the market equilibrium) and a permanent shock treatment (where three shifts in the demand curve occur). The price in the experiment was determined by the following market equilibrium equation:

$$D(p_t) = \frac{1}{K}\sum_{i=1}^{K} S(p_{i,t}^{e}),$$

where $K$ is the size of the group and the others notations stand for the usual variables. For all treatments they used the following specification for demand and supply:

$$D(p_t) = a_t - bp_t$$

$$S(p_{i,t}^{e}) = \tanh(\lambda(p_{i,t}^{e} - 6)) + 1$$

The main results that they obtain are the following:

*i)* *Average earnings in multi-agent treatments are much more higher than the average earnings in the corresponding single-agent treatments*; this result can be explained by the fact that in the single-agent treatment a subject who is able to learn can expect very high earnings, whereas a subject who is not able to learn will have an almost null gain (only 34% of agents do learn); in multi-agent treatments every good (bad) individual price prediction is compensating by the other predictions, leading to a medium realized market price.

*ii)* *The experimental outcome may be described as a boundedly rational heterogeneous expectations equilibrium where price predictions are correct on average, prices converge to RE in the mean and diversity of beliefs leads to excess price volatility along irregular, unpredictable price fluctuations.*

**Van de Velden(2001)**

In 2001, Van de Velden published his PhD thesis on expectation formation in dynamic economic systems. In this thesis, he analysed a cobweb market and put it into perspective with an asset price market (negative versus positive feedback).

The part of the thesis related to the cobweb model contains three experimental chapters with a single-agent treatment, a multi-agent treatment and a strategy approach to expectation formation are analyzed. Those chapters are extensions of his joint work with the other members of the team presented in Sonnemans *and al*. (1999) and Hommes *and al.* (1999).

**Heemeijer *and al.* (2004)**

Heemeijer *and al*. (2004) designed an experiment in order to *compare expectation formation in negative and positive feedback systems* (a cobweb and an asset price model). The most important objective of the experiment has been *to derive explicitly the prediction rules actually used by the participants* in both treatments. Their assumption is that humans, instead of being fully rational, use some kind of bounded rationality to form price expectations, likely to not vary according to the economic environment they are confronted with. The following price adjustment formula was used (including the time lag) in order to create a full symmetry between negative and positive feedback treatments:

$$p_t = p_{t-1} + \lambda\left[D(p_{t-1}) - \sum_{h=1}^{H} n_{h,t} S(p^e_{h,t})\right] + \varepsilon_t$$

The authors provide a full analysis of their results. Their experiments show that:

*i)* *The ability of individuals to choose an appropriate form of bounded rationality is likely to be limited*, since most participants, whatever the shape of their economy, choose their prediction rule from a highly restricted and simple set of rules.

*ii)* *The two treatments of the experiment have produced series of market prices with clear qualitative differences*. In the cobweb groups, prices tend to go through an initial phase of high volatility, neatly converging afterwards to the fundamental price, only to be disturbed occasionally by the impact of a mistake by one of the group members. In the asset pricing groups, volatility in the beginning lasts for a much shorter period, but also is not followed by a quick convergence to the fundamental price. Rather, most groups demonstrate a slow oscillatory movement around the fundamental value, which seems to come very close to it only in the long run. A short and general way of describing the market price development in the cobweb treatment is therefore "*slow coordination and fast convergence*", and in the asset pricing treatment "fast coordination and slow convergence". These labels are at odds with the REH in this context, which requires market prices to be a white noise process around the fundamental value.

*iii)* *Price predictions are very close to each other*, resulting in small differences in earnings within groups, as compared to significant deviations in aggregate earnings between them.

*iv)* Cobweb treatment participants can be best described as "*naive fundamentalists*".

### 5.3.4. Empirical research: conclusion

We review in this section the experiments that have been run on the cobweb model. To give a brief synthesis on this empirical work, we can make several categories in order to classify these experiments:

*i)* a categorization can be made according to the amount of information that is delivered to the participants at the beginning of the experiments (concerning the market equations) or between rounds (concerning individual and aggregate results of a period); the experiments deliver, starting from a zero-information case, different amounts of information, but never full information;

*ii)* another way to differentiate the experiments is to separate them into linear and non-linear markets;

*iii)* linear or non-linear function can or cannot be presented under the form of step functions;

*iv)* the market can be expectation or production driven (market price is determined either by forecast or production decisions); when the market price is simply determined by the total production, a single commodity market or a market with several commodities can be experimented;

*v)* the experiments' aim is either to investigate expectation formation or the stability of the equilibrium;

*vi)* markets can be populated with one single agent or with several participants;

*vii)* the market can run once, several rounds or for a high number of rounds;

The main results stipulate better results in multi-agent markets, and evidence of rationality in decisions, independently of the type of market under scrutiny and of the information characteristics. Moreover, strategies are likely to become more complex with time. There is strong evidence of the convergence to an REE point, independently of theoretical characteristics, but conclusions on beliefs coordination are more mitigate.

Our experimental work will therefore introduce the following elements: full information about the market equations and about aggregates and personal results between periods; linear function presented as step functions; multi-agents markets; production driven markets with(out) elicited beliefs; markets with a single commodity; 40 rounds of interaction between homogeneous players. In these experiments, we will analyse the process of expectation formation and the conditions of stability of the equilibrium.

## 5.4. Concluding remarks

In this chapter we analytically presented the linear cobweb market, together with several theoretical models addressing the expectations formation and with empirical experimental research. The cobweb model is part of the family of models that assume a supply–response lag, i.e. an interval of time between the date when the suppliers decide how much to produce and the date when the supply actually become available on the market exists, like non-storable goods, crop, etc. Once the supply becomes available on the market, it is assumed in all these models that the market is immediately cleared: the price adjusts immediately to the existing demand. When deciding of the amount that will be supplied to the market, suppliers have to form expectations of the future price (in turn is influenced by past prices) and base their production decisions on these expectations: since it takes one time period to produce the good, the production decision of the suppliers depends on their expectation of the price that will prevail on the market. Because of that, market is driven mainly by price predictions and resulting production decisions of the suppliers, rather than by comparable predictions and decisions of consumers. The traditional graph of a cobweb economy is characterized either by the "cobweb" cycle, either by temporal fluctuations. Increasing price predictions lead to increasing production, a decreasing excess demand and therefore lower prices, causing tendencies in expectations to produce a reverse effect in market prices (negative feedback). It is important to know how expectations are formed. In this first part of the chapter we reviewed the formalization of the linear cobweb model with homogeneous agents. In this model, a unique equilibrium can either be reached by past data observation or by eduction. Under particular values of the parameters, this system is stable independently of the expectation rule used to describe its dynamics. According to the type of rule assumed to drive the expectation formation, the convergence process takes place in real or in notional time. When the convergence operates at one remove, this is the consequence of a complex collective introspective reasoning, called *eduction*, where individuals *forecast the forecast of the others* in steps. If they possess the ability to put into practice this reasoning ad infinitum, they act according to the REH described by Muth (1961). If they are likely to put into practice only a finite number of steps of eductive reasoning, they *i)* partially understand the REH assumptions because their cognitive constraint is binding or *ii)* they estimate that their opponents will only put into practice a finite number of steps of eductive reasoning (based on this estimation, they impose their own limits). A conceptual distinction can be made between the first case (*i*) and the second (*ii*), by saying that their rationality is limited (taken as given) or finite (self-imposed). When the convergence operates in sequential steps visible at each round or period, individuals observe past data and revise their beliefs accordingly. The process of expectations formation cannot be simply described by simple mechanical forecasting rules because individuals are likely to take into account not only past observations of the market variables, but also to learn from their mistakes.

The linear cobweb market has the same internal structure as a beauty contest game with negative feedback. As negative feedback operates in a cobweb model, the market is stabilized. In our experiments in chapters 6, 7 and 8, we will try to address the question of the *type* of reasoning that participants are likely to use in a cobweb market and to *which extent*. Empirical work addressing the expectations formation process has made the distinction between full informed/non-informed markets, single/multiple agents markets, linear/non-linear markets, expectations/production driven markets etc. The main results stipulate better results in multi-agent markets, and evidence of rationality in decisions, independently of the type of market under scrutiny and of the information characteristics. Moreover, strategies are likely to become more complex with time. There is strong evidence of the convergence to an REE point, independently of theoretical characteristics, but conclusions on beliefs coordination are more mitigate.

**Contents**

# Chapter 6

# Price forecasts and coordination by the beliefs in an experimental cobweb market

## 6.1. Introduction

According to the rational expectations hypothesis, the assumption of rational behaviour can be extended to beliefs formation (Muth, 1961). On average, agents make correct forecasts because it is in their own best interest to act in this way. In equilibrium, all agents hold exactly the same expectations, i.e. expectations are perfectly coordinated beliefs. This hypothesis relies on two fundamental principles: bayesian rationality and common knowledge of rationality. The implication is that agents are induced to take actions whose aggregated outcome matches exactly their expectations.

While the underlying reasoning sustaining this type of equilibrium is well known, it remains an empirical issue to know whether agents are able to coordinate their beliefs and take actions that exactly confirm their beliefs. For example, does learning through repeated market interactions orient belief formation in the direction of a common expectation? Do coordination failures lead to an updating of the process of belief formation favouring coordination?

In this chapter we present results of experiments whose objective is to investigate belief formation and reasoning in a dynamic market. These experiments were led in the simplest dynamic market model, the cobweb model. Let us remind that the cobweb model predicts price adjustments in a market of a non-storable good. Output decisions must be made one period before the production is sold on the market. Therefore, upon making their production plan, producers must anticipate the price at which their output will be sold. Ex post, the selling price is determined according to the demand schedule and the aggregated output.

The Rational Expectation (RE) hypothesis assumes that agents form their beliefs by relying on all available information. Furthermore, they know perfectly the market equilibrium equations. Two different justifications of the RE hypothesis are generally put forward: we call them hereafter *adaptive* and *eductive* justification respectively. The *adaptive justification* relies on the repeated interaction among agents and on the induced learning possibilities: in feedback learning a myopic best-reply guides the agents' behaviour towards the rational expectation outcome. The *eductive justification* relies on an individual mental process: reasoning about the logic of the situation ("forecasting the forecasts of others", Binmore, 1987), leads rational agents to eliminate dominated outcomes. This chapter is primarily motivated by investigating the predictions of the eductive justification. In the linear cobweb model (Guesnerie, 1992) eductive reasoning leads, through the iterated elimination of dominated strategies (the "tâtonnement" of the cobweb in notional time), to the convergence (divergence) towards the equilibrium price.

The main hypotheses that we try to address in this chapter are: *is convergence likely to be faster under particular values for the market equations parameters? Do small (large) sized markets perform better in reaching the REE than large (small) sized groups?*
In order to address these questions, we investigate several other hypotheses: *do we observe coordination with time (emergence of similar profiles and learning)? Are participants, endowed with perfect knowledge about the market, able to perfect forecast it? Do they hold expectations coherent with their decisions? What happen in cobweb markets where theoretically chaos is expected? Do participants reach the REE? Do they put into practice some simple forecasting rules or do they sophisticate their reasoning when taking decisions?*

In section 6.2 the experimental design will be described; section 6.3 will present results for our main treatments; additional results on the stress conditions will be given in section 6.4 and a general discussion and conclusion will be presented in section 6.5.

## 6.2. Experimental design

Let us remind the structure of the cobweb model: as we deal with linear functions, the basic equations are:

$$D(p_t) = A - B\, p_t$$

$$S(p_t^e) = C\,p_t^e + D$$

with *A, B, C, D* parameters. The supply function is positively sloped, i.e. $C > 0$, and the demand function is negatively sloped, i.e. $B > 0$.

There are *N* identical producers on the market, and the marginal cost of each of them is given by:

$$MC(q_t) = \frac{q_t}{c} + d.$$

Equilibrium occurs when price equals marginal costs, and through the realization of this program we obtain the preceding aggregate supply function. The equilibrium obtained by the intersection of the demand and supply functions coincides with the RE and the Nash equilibrium. In particular, this is the price obtained through collective introspection, i.e. eductive reasoning. This equilibrium is the finality of an infinite process developed in *steps*. Our research aims at measuring the ability of agents to compute these steps to the REE and, if the process were not to be complete, our attempt would be to find why do agents stop sophisticating and after how many steps. Let us remember that this equilibrium is $p_n = \frac{A-D}{B} \times \frac{1-(-1)^n\left(\frac{C}{B}\right)^n}{1+\frac{C}{B}} + \frac{A-D}{B} \times (-1)^n \left(\frac{C}{B}\right)^n p_o$, whose limit is $\frac{A-D}{B+C}$.

So fundamental parameters that we have to choose to define the participants profile in the cobweb market and other market characteristics are: *c, d, N, A* and *B* and our principal question is about the value of *n*. Several constraints have to be taken into account for the choice of these parameters: for example, the equilibria and social optimum strategies have to be integers, and far from "focal points": mid-interval choices, collusive or oligopolistic strategies etc.

We will first describe the experimental parameters and after the experimental procedures. At the end of this subsection we will summarize the experimental design.

### 6.2.1 Experimental parameters

All treatments in this experiment are interdependent: each treatment is thus defined in direct connexion with another (usually called the benchmark case), by keeping all parameters stable except for one parameter. In this subsection we will explain our choices for the fundamental parameters defined earlier.

**Number of steps of convergence**

The supply and demand schedules were defined in discrete (integer) units, so that each producer had to choose an integer valued output level. With this setting, aggregate supply and demand curves are step functions. The implication is that eductive reasoning leads to the equilibrium point in a finite number of iterations instead of the infinite number of reasoning steps as presented earlier. Furthermore, we can manipulate the number of steps by changing the shape of the supply or the demand curve.
The intuition is that with a smaller number of reasoning steps subjects can find the equilibrium more easily. A similar design was used by Ho and al. (1998) in the guessing game to investigate the assumption that equilibrium beliefs will be easier to attain for a small number of iterated dominance steps. They found that finite-step games get closer to the equilibrium than infinite-step games. Recall that iterated elimination of dominated strategies leads to the equilibrium in the linear cobweb model only if he condition $B > C$ is met.

We consider two treatments under such a condition. $B$, the slope of the demand function is held fixed, and we vary $C$, the slope of the supply curve. As the value of $C$ increases and comes close to $B$, the number of iteration increases. For a large difference $B – C$, the number of iterations is small, for small differences the number of iterations will be large. We therefore consider a small value for $C$ and a large value for $C$. Since for a small value of $C$ the number of iterated dominance reasoning steps is also small we hypothesize that subjects will have less difficulty to coordinate on the equilibrium belief. By repeating the market many times, our conjecture is therefore that if ever the realized price convergences towards the equilibrium price over time, the process will be faster for low $C$ than for large $C$.
Since $B$ is fixed in our experimental design, the treatment with low $C$ (large difference $B – C$) will be called *fast convergence* condition and the treatment with large $C$ (small difference $B - C$) will be called *slow convergence* condition. We also investigate an additional treatment for which $B - C < 0$. Theoretically, under this condition the equilibrium is never reached, since eductive reasoning leads to divergence. We call this treatment the *divergence* condition.

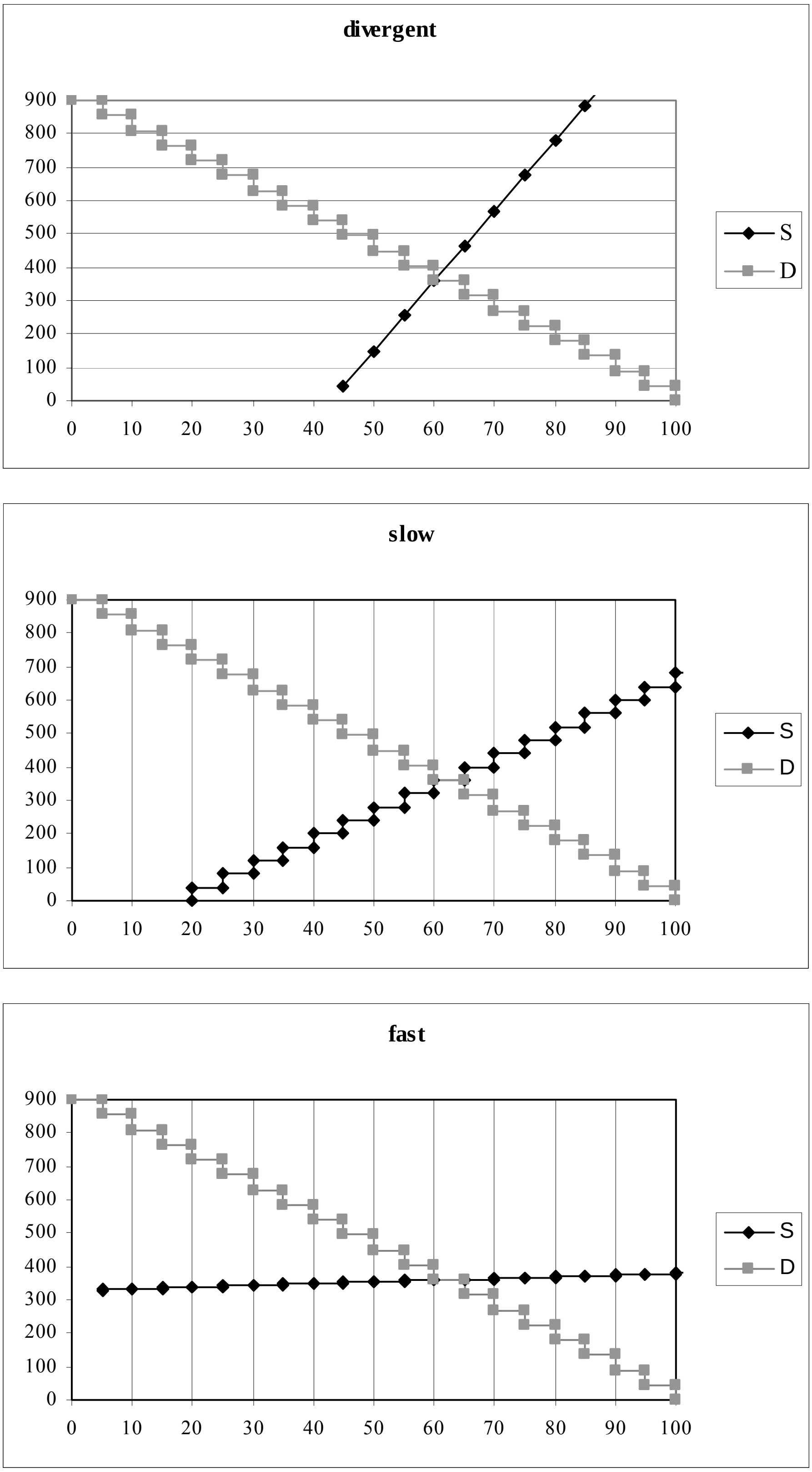



Figure 6.1. Experimental treatments
(prices on the horizontal axis and total quantities on the vertical axis)

### Available information

Subjects in these experiments have full information about the underlying market equations and mechanisms and about their role in the market and the consequences of their decisions. The information in the experiment is therefore similar to the information assumption in Muth (1961) about the formation of the REE, namely that all information is available and is common knowledge: it was common knowledge to the subjects of each session that the individual marginal cost functions and the demand functions were identical and that all subjects received the same instructions. In other words the subjects knew that all subjects in a market had the same information, the same characteristics and were required to make the same type of decisions simultaneously. But, while subjects have complete information on the rules of the game and in particular on each player's payoff function, they do not know the other subjects' motivations and degree of rationality. Therefore we decided to put into practice markets with theoretically homogenous players; according to each player behaviour and understanding of the market equations, heterogeneity will be endogenous and we didn't wanted to increase it.

### Decisions to take

Subjects had two decisions to take: a production decision and a forecast decision. Subjects were required to announce their market price forecast in addition to their output decision. Price forecasts were made by choosing a number between 0 and 100 in multiples of 5 and quantity decisions were made by choosing integer numbers between 0 and 900. The decisions are simultaneous. Incentive schemes are put into practice for each type of decision.

### Size of the market

In the theoretical framework of Guesnerie (1992), the eductive reasoning argument states that there is a continuum of agents participating in the cobweb market. Each one is concerned only with his own action and with aggregate data, i.e. total production and realized price, and every agent has (if any) only an infinitesimal influence on these variables. When the theoretical model is transposed into an experimental market, the number of subjects participating to a single market has to be finite. Davis and Holt (1993) presented a classical result from double-auction markets, where having two participants on each side of the market is enough for them to behave as stressed by the pure and perfect competition rules. In experiments were subjects transact on only one side of the market, a small sized group could induce a collusive behaviour. Therefore we chose to investigate both a small and a large group size. In accordance with the existing experimental literature on the cobweb market cited earlier, we will have small markets of five participants and large markets of ten participants.

| | | Convergence condition | | |
|---|---|---|---|---|
| | | *Fast* | *Slow* | *Divergence* |
| Group size | *Small* | 6 | 6 | 6 |
| | *Large* | 2 | 2 | 2 |

Table 6.1. Independent large and small markets

**The cost function**

Subjects received written instructions containing detailed information about the aggregate demand function and their individual marginal cost function. The demand function is decreasing with price and the marginal cost function increasing with price. The demand and cost functions are presented to subjects as tables. The levels of individual output are grouped into intervals of homogeneous size in each treatment. The size of these intervals differed according to the convergence condition (1 for the *fast* condition, 8 in *slow* condition and 20 for the *divergent* condition). Therefore the number of steps is not equal across conditions[1]. The last interval of individual output was an open interval. To each interval corresponded a different level of marginal cost, in multiples of 5. The range varied according to the convergence condition in order that the equilibrium price and quantity remained constant across treatments[2]. Table 2 summarizes the parameters values that were chosen for the different treatments.

[1] 14 output intervals for the *fast* condition, 21 for the *slow* condition and 16 for the *divergence* condition.
[2] The range of marginal cost was 10 to 140 for the *fast* condition, 20 to 120 for the *slow* condition and 45 to 120 for the *divergent* condition.

| | *fast* | *slow* | *divergent* |
|---|---|---|---|
| *A* | 900 | 900 | 900 |
| *B* | 9 | 9 | 9 |
| *C* | 5/10 | 8 | 21 |
| *D* | 330 | -120 | -900 |

Table 6.2. Aggregate parameters of the experimental treatments

Subjects knew that the sum of the individual productions determined total output, and that the output had to be sold within the period, so that the selling price was determined according to the demand schedule.

**The demand function**

The aggregate demand function is defined on { 0,1,…900 }. This function is identical for all the treatments, as indicated in table 2. The upper limit of this interval determines the capacity of the market or the total output (for a higher quantity the selling price is zero). All possible choices for the total output are divided into 21 homogeneous intervals of amplitude 45 units. Each interval of total output determines a selling price. This implies that there are 21 possible prices on the market, in multiples of 5. The maximum price is obtained for a zero demand and it is equal to 100. The subjects had a table for the demand function specifying, for each interval of total output, a price within the set {0, …, 100} corresponding to aggregate output levels in the set {0, …, 900}(see Appendix).

**Profit functions**

We implemented a quadratic scoring rule to guarantee the truthful revelation of beliefs is incentive compatible. The reward for correct forecasts was a flat rate of *F* experimental currency units. This amount was reduced in proportion of the forecasting error according to a quadratic error term:

$$\Pi_{f\,t} = F - 0{,}8 \times (p^e_t - p_t)^2,$$

$\Pi_{f\,t}$ represents the profit or loss of the forecast, *F* is the amount obtained for a perfect forecast (it takes the value 1000 in small groups and 500 in large groups), $p^e_t$ is the price forecast for period t and $p_t$ the prevailing selling price in period $t$. The profit obtained from forecasting was added to the profit resulting from the output decision defined in the standard fashion:

$$\Pi_{q\,t} = q_t \times p_t - TC\ (q_t),$$

where $\Pi_{qt}$ is profit for the current period, $q_t$ the subject's output choice and $TC$ the total production cost. $\Pi_{qt}$ can be positive or negative, according to values taken by the prices, rising from the aggregation of the individual decisions.

We define an *earning ratio* $r_t = \dfrac{\pi_{qt}}{\pi_{ft}}$ measuring the relative output earnings for period $t$, and we note $\bar{r}$ the average earning ratio. In large experimental markets producers are small with respect to producers in small sized markets. Therefore, REE individual production earnings are up to two times lower in large market; in order to keep the belief elicitation activity incitative, we kept $\bar{r}$ constant over treatments, i.e. perfect forecast earnings are twice lower than in small sized economies. Note that at the REE, since there are no forecast errors, $\Pi_{ft}$ = 1000 in small sized groups and 500 in large sized groups and $\bar{r}$ is given by table 6.3:

| | | *fast convergence* | *slow convergence* | *divergence* |
|---|---|---|---|---|
| $\bar{r}$ | *small* | 3.4 | 1.4 | 0.4 |
| | *large* | 4 | 1.44 | 0.3 |

Table 6.3. Predicted value of the earning ratio according to treatment.

The elicitation of price forecasts should favour the coordination and the convergence in the cobweb model, especially because price forecast are rewarded according to the quadratic scoring rule. This should lead subjects to coordinate their beliefs and move therefore faster to the equilibrium price.

**Position of the equilibrium**

Using a backward induction argument (Selten, 1975), if the constituent game has a unique Nash equilibrium, then the finitely repeated game has a unique sub-game perfect equilibrium, the sequence of the static equilibrium: the static equilibria will serve as benchmarks for the repeated game analysis. This subsection describes the theoretical predictions for the *one-shot* game. Inside a period, the equilibrium price satisfies the condition:

$$A - B\,\overline{p} = C\,\overline{p} + D\,,$$

giving us the value:

$$\overline{p} = \frac{A-D}{B+C}$$

and the equilibrium quantity supplied becomes:

$$\frac{AC+BD}{B+C}.$$

Therefore, in all treatments (for all values of the parameters *A, B, C, D*), the market equilibrium is the same. It occurs when market price equals 60 and total supplied quantity is 360 units. Thus it corresponds in small size markets to an individual production of 72 units and in large size markets to an individual production of 36 units. This equilibrium is far from the mid-interval choice and from Cournot and collusive equilibrium. Let us note that in Cournot equilibrium, the price does depend on the individual quantity sold on the market, therefore in a symmetrical framework the profit to be maximized is $\Pi_{qt} = q_t \times \frac{A - Nq_t}{B} - \frac{q_t^2}{2c} - dq_t$, which gives the value $q_{Cournot} = \frac{c(A-Bd)}{2Nc+B}$; in the collusive setting, the profit to be maximized is the joint profit $\frac{Nq_t(A-Nq_t)}{B} - \frac{N^2 q_t{}^2}{2c} - Ndq_t$, which gives the value $q_{coll} = \frac{c(A-Bd)}{N(2c+B)}$. Therefore, in order to reach the Cournot equilibrium, with the given parameters values, a 5% deviation from the REE should occur in the fast case, a 32% deviation in the small case and a 41% deviation in the divergent case. In order to reach the collusive equilibrium, on average higher deviations have to occur (between 65% and 89%).

**Number of periods**

All previous theoretical predictions are static predictions. In the experiment, each constituent game is repeated 40 times, and this is common knowledge. We chose such a design because in the field, the interactions between producers and the market are likely to exist for several periods.

**The initial endowment**

As negative production and forecasts payoffs are possible, in each experimental market subjects received an initial endowment to avoid them bankruptcy. When subjects' earnings become negative control over induced preferences is lost because negative payoffs are not credible. In particular, subjects may exhibit risk seeking behaviour in this situation. This endowment was set at 10 euros in all small sessions and at 5 euros in all large sessions; in one session (corresponding to the 3 markets of the treatment called *slow high*), the initial endowment was 20 euros. Subjects whose payoffs are still accidentally negative only received a show-up fee.

### 6.2.2. Experimental procedures

The experiments were conducted at the LEES laboratory in Strasbourg between July 2002 and July 2003, on the basis of a computer network, based on an application developed by Bounmy (1998). A total of 180 subjects participated in these experiments[3]. Subjects involved in this experimental test were inexperienced, i.e. they had never participated before in a similar experiment. A total of 11 sessions was carried out. Each session involved 15 or 20 subjects interacting during 40 periods in cobweb markets as described previously. They were split into 5 or 10-subjects independent groups of "producers", unchanged over the 40 periods (this type of framework is called "partner", as opposed to a "stranger" one, where the groups change at each period). Thus during this experiment we developed 30 independent markets with characteristics differing according to the experimental parameters values. All parameters were common knowledge in the experiment and fixed during the experiment. In particular, the subjects knew that the game is perfectly symmetric. Communication between subjects was not allowed (in the laboratory players were separated by partitions). Each subject received the same written instructions (see Appendix); within a group, players were homogenous; they had time to read instructions carefully and the experimenter also read them aloud once that all subjects finished reading them by them own. We used a neutral wording for the instructions in order to limit uncontrolled psychological effects. Therefore, subjects only know that they are producers who have production costs and sell on a market; no reference is made to the kind of product, firm, etc. At the beginning of the experiment subjects received a fixed endowment of

[3] The participants in the sessions were students, randomly selected from a large subject pool of 1500 volunteers. The pool includes students from all disciplines from the universities of Strasbourg and is refreshed every year; the experimental history of each subject his recorded, together with individual data.

currency units, called *capital*. The initial capital was constant across treatments (except for one extra treatment). The experiment lasts for 40 periods or rounds. Each subject had to take two decisions per round. After each period earnings were added to the initial capital and losses were subtracted. At the end of each period, subjects were informed about the prevailing selling price, their production cost, their forecast and production earnings (their profit or loss), and the remaining capital. Then a new period started and turned out in a similar way. Furthermore, subjects could see at any time their individual past data by clicking on a *history* button. Each session begun with two trial periods in order to familiarize subjects with the graphic interface. The subjects' understanding of the instructions and procedures was checked by a computerized questionnaire (consisting of ten questions) submitted before the beginning of the experiment. If a player came out with a wrong answer, he was given individual explanations by the experimenter. During the experiment, the subjects could make written comments on a paper sheet. At the end of the experiment, they received the amount of money corresponding (after transformation of the experimental capital into real money at the settled exchange rate) to their cumulated payoff. They earned between 6 and 30 euros for an average time of 90 minutes per session.

### 6.2.3. Synthesis of the experimental design

In this chapter we address the question of expectation formation within a cobweb market, by conducting several treatments summarized in table 6.4. Two main distinctions operate in this chapter: a distinction between the slopes of the supply curves, theoretically implying our *fast, slow* and *divergent* categories; a distinction between a large and a small group size setting, giving us the categories *small/large*; in addition, we use three stress treatments to briefly investigate some limit conditions. These experiments implicated 195 inexperienced participants and took place in 2002 and 2003 at the LEES laboratory in Strasbourg.

| Treatment | Size of the market | Initial endowment | Number of independent markets | $c$ | $d$ |
|---|---|---|---|---|---|
| Fast small | 5 | 10 | 6 | 0.1 | -660 |
| Slow small | 5 | 10 | 6 | 1.6 | 15 |
| Divergent small | 5 | 10 | 6 | 4.2 | 300/7 |
| Slow high | 5 | 20 | 3 | 1.6 | 15 |
| Fast zero | 5 | 10 | 3 | 0.1 | -660 |
| Fast large | 10 | 5 | 2 | 0.05 | -660 |
| Slow large | 10 | 5 | 2 | 0.8 | 15 |
| Divergent large | 10 | 5 | 2 | 2.1 | 300/7 |
| Divergent limit | 5 | 10 | 3 | $\infty$ | 60 |

Table 6.4. Synthesis of the experimental design

## 6.3. Experimental results

In these experiments, the subjects have two decisions to take and each decision is rewarded. The results of their decision are, on the one hand, their earnings; on the other hand, the realized market price: they take two decisions who enhance two "outputs". Therefore, this section will be split into four subsections, successively analysing earnings, market prices, forecasts and production decisions.

### 6.3.1. Profits

In this subsection we present the results on earnings; as the subjects had to take two decisions (and were rewarded accordingly), our aim is to compare earnings profiles for both types of decisions. Production earnings analysis allows us specifically (but not exclusively) to test hypothesis on learning, while forecast earnings will give us indicators about the quality of predictions and about beliefs coordination. Moreover, as in this experimental design we check for the main differences in subjects' behaviour in treatments with small/large groups, in the presentations of this subsection we will present the results accordingly.
This subsection on profits will thus be constructed on comparisons, *i)* between large and small groups and *ii)* between forecast and production earnings.

**The quality of predictions**

Recall that forecast earnings are based upon the quadratic scoring rule, i.e. forecast profit $\Pi_{ft} = F - 0.8 \times (p^e_t - p_t)$, whose maximum $F$ is reached for a perfect forecast of the market realized price ($F$ takes the value 1000 in small groups and 500 in large groups). Therefore, the lower the difference between $p^e_t$ and $p_t$, the higher $\Pi_{f\,t}$, i.e. the higher the quality of the forecast, the higher the forecast profit. As a good forecast implies a high profit, it follows that we can test the quality of forecasts by evaluating the forecast profits. Average forecast profits (per subject and per period) are summarized in the next table for small and large treatments. The first rough evidence is that with time, the average forecast profits (i.e. the quality of predictions) increase, whereas the standard deviations (i.e. the differences between players) decrease. The second observation is that in large groups the quality of the forecasts is lower than in small groups, and that holds as well in the first part of the experiment as in the last part: for the 20 first periods, subjects in large groups only reach 41.4% to 62.2% quality in predictions, whereas those in small groups arrive at a quality between 78.4 % and 92.7%; the quality of large groups forecasters improves with time, but still remain at a lower level comparing to small groups subjects (for the last 20 periods, in large groups the quality of the forecast is between 89.4% and 92.8%, while in small groups it is between 96.2% and 98.4%).[4]

| | | fast | | slow | | divergent | |
|---|---|---|---|---|---|---|---|
| | | *small* | *large* | *small* | *large* | *small* | *large* |
| periods 1 to 20 | $\bar{\pi}$ | 914 | 273 | 927 | 311 | 784 | 207 |
| | σ | 294 | 197 | 259 | 183 | 653 | 215 |
| periods 21 to 40 | $\bar{\pi}$ | 973 | 447 | 984 | 462 | 962 | 464 |
| | σ | 100 | 112 | 21 | 54 | 129 | 57 |

Table 6.5. Average forecast earnings (per subject and per period)
and standard deviations in points

It seems that, in large groups, subjects meet more difficulties to make a perfect forecast of the market price. Therefore, it still remains relatively high differences between them (except for the divergent groups, standard deviations are always higher in large groups).

[4] $p<0,005$.

The decreasing differences between players and improving quality of their predictions can occur only in the neighbourhood of the perfect forecast (the reference point), thus this result can be interpreted as revealing the forecast coordination. We thus put forth the assumption of a success of the coordination by the beliefs, to be confirmed by further analyses. This coordination is done within a more symmetrical framework in the two convergent cases and reveals some differences between the players in the divergent treatment (see the standard deviation for the first subperiod). This result is significant insofar as the agents should not coordinate in the divergent case and the following analyses will try to explain it.

**Output profits**

Table 6.6 summarizes our observations in terms of average output profit ($\overline{\pi}_q$) and standard deviations ($\sigma$) for the first 20 periods (1-20) and for the last 20 periods (21-40). Averaging over the two sub-periods allows us to detect a rough effect of learning and to verify efficiency. As we see from table 6.6 our rough indicators already show the effect of learning with repetition. First, the average profit from the production activity increases with repetition, for all treatments[5]. In all groups (except one large slow group), average output earnings in the second subperiod (21-40) are close (and sensibly higher) to the predicted REE earnings.
Second, we observe that the variability of profits decreases sharply from the first sub-period to the second. In other words, individual differences decrease with repetition which suggests that subjects' choices become closer to each other in the second half of the experiment than in the first half. This observation is a proof of coordination.

In the divergent case, the average profit level is much lower than in the two other treatments, in both time-intervals. However, the evolution of the average profit level shows as in the two other treatments, a convergence of the profit as time evolves, around 900. This reveals that subjects were successful in coordinating their output choices, although they coordinated on a low level of profit. If the performance of the production profits in the divergent case is due to the success of coordination by the beliefs, since the divergence case stands in obvious contradiction with eductive reasoning, is must be the case that subjects were able to coordinate by relying on a rule different from sophisticated reasoning. It could also be the

[5] this is supported by a Wilcoxon rank sum test ( $p<0,03$)

consequence of an exploitation of the possibilities offered by the market and of a quartering in a type of strategy providing high profits (*underreaction*).

| | | fast | | slow | | divergent | |
|---|---|---|---|---|---|---|---|
| | | *small* | *large* | *small* | *large* | *small* | *large* |
| periods 1 to 20 | $\overline{\pi}_q$ | 2685 | 1053 | 1433 | 391 | 224 | -163 |
| | $\sigma$ | 5388 | 1858 | 2116 | 582 | 6079 | 667 |
| periods 21 to 40 | $\overline{\pi}_q$ | 3439 | 1972 | 1662 | 786 | 813 | 283 |
| | $\sigma$ | 632 | 294 | 385 | 107 | 720 | 78 |

Table 6.6. Average earnings and standard deviation (production)

**Learning and coordination potential**

From the last two tables we noticed that, in general, with time, average earnings increase, while standard deviations decrease. We interpreted this result as en evidence of learning and coordination. However, there are groups and treatments where the subjects seem to learn and coordinate quickly, i.e. differences are more accurate or more patent. We thus aim at calculating the learning and coordination potentials rates ($i_{j,k}$). These rates are calculated as follows:

$$i_{j,k} = \frac{\overline{\pi}_{(21-40),j,k}}{\overline{\pi}_{(1-20),j,k}},$$

where $j = \overline{with, without}$ and $k = \overline{fast, slow, divergent}$, and $\pi$ stands either for output or forecast earnings.

Table 6.7 reports the average forecasts and output profit increases for all treatments. When we displayed the precedent results on earnings, we reported the detection of a learning or coordination effect each time that earnings in the last time of the experiment were larger than first part profits. As we observed a generalized increase in profits with time, we expect that all those rates be larger than 1 (this is the case).

| | (a) | | (b) | |
|---|---|---|---|---|
| Size of the group | *large* | *small* | *large* | *small* |
| *Fast convergence* | 1.63 | 1.06 | 1.87 | 1.28 |
| *Slow convergence* | 1.48 | 1.06 | 2.01 | 1.15 |
| *Divergence* | 2.24 | 1.22 | 2.73[6] | 3.62 |

Table 6.7.Average growth rate of (a) forecasts and
(b) output profit per treatment

Another observation was that initial earnings (relative to the REE) in large groups were lower than the corresponding earnings in small groups. This result is confirmed by the growth ratios, indicating that a higher learning and coordination potential is detected in large groups compared to small groups: all ratios are higher in large groups.[7](the large divergent treatment ratio is particular insofar the initial value is negative). As in large groups the starting point is lower, there are more possibilities to improve performances; similarly, in small groups subjects are from the beginning good forecasters and clever in production decisions, therefore they cannot improve too much. The main conclusion is that in all groups and all treatments there is a learning and coordination potential, exploited by the participants because it improves their earnings.

**Learning estimators**

Once the coordination is achieved into a group, subjects remain coordinated because it corresponds to a dominant strategy and any individual deviation from what "the average opinion expects average opinion to be" (Keynes, 1936) is costly: a deviation on forecast is not only a coordination failure, but also getting lost from the REE way. In that sense (as hitting on the perfect forecast is a focal point) coordination is less difficult than learning. Learning needs to occur in steps and in order to bypass these steps subjects have to use the possibilities offered by the market environment. Deviations are much likely because the steps chain can be broken simply by the saturation of the cognitive constraint of some participants. We thus verify in this paragraph whether subjects in each group make use of the average learning potential detected earlier. Testing if this potential is put into practice within a group, it is equivalent to verifying the significance of the previous indicators. Therefore we set up a more refined analysis of learning by taking into account the 40 periods. In order to do so, for all

[6] in absolute value.
[7] $p<0.005$

groups, all treatments and all periods, we introduce the *time* variable in a regression on past realized prices, to predict the average output profit of a group, as follows:

$$\Pi_{q\,t} = \beta_1 p_{t-1} + \beta_2\, t + \varepsilon_t,\ t=\{1,\ldots 40\}$$

In order to detect learning, the coefficient of the time variable ($\beta_2$) should be significant and positive, i.e. the average output profit increases with repetition due to learning. Table 6.8 summarizes for our 24 groups, and all treatments, the significance level for the *t*-test. When a negative sign is found for the *t*-test, the coefficient $\beta_2$ of the time variable is also negative (negative, as well as non-significant coefficients, appear in italics in the table). For almost all the groups, the time variable is significant and exhibits positive coefficients, partly proving learning. It seems that in divergent groups the learning task is the most difficult, as they present most of the non-significant or non-positive coefficients.

| | | fast | | slow | | divergent | |
|---|---|---|---|---|---|---|---|
| | | *small* | *large* | *small* | *large* | *small* | *large* |
| *group* | *gr1* | 2.86 | 4.85 | 3.59 | *0.07* | *-1.21* | 2.20 |
| | *gr2* | 5.35 | 2.46 | 3.96 | 2.57 | *0.27* | 2.12 |
| | *gr3* | 4.42 | | 2.08 | | 2.16 | |
| | *gr4* | 4.74 | | *1.44* | | *0.64* | |
| | *gr5* | *0.76* | | 2.10 | | *1.12* | |
| | *gr6* | 3.12 | | *1.80* | | *-1.38* | |

Table 6.8. Significance levels (*t-test*) and sign (+/-) for time variable

### Comparison of forecasts and output earnings

Comparing the tables on production earnings with the related tables on forecasts earnings, it appears that the coordination in forecasts is faster than the coordination in production decisions, whereas, theoretically, the timings of coordination in both decisions should be correlated. Next graphs depict the evolution of the average earnings during the experiment. While production earnings graphs exhibit volatility even in the last part of the experiment, forecast earnings are smoother. The correlation of the decisions is apparent only in the very first periods of the experiment (when the market is still unstable) and in situations of market crash (when a single "foolish" action from an agent can drive the market to a price equal to zero; this happens only once after the preliminary period of ten periods, when the situation occurred three times). The general trend is to a flat rate in forecast earnings and to an oscillating profile in output earnings. We thus can already state that the subjects concentrate more on the forecast than on production (forecasting is an easier task because of the focal point).

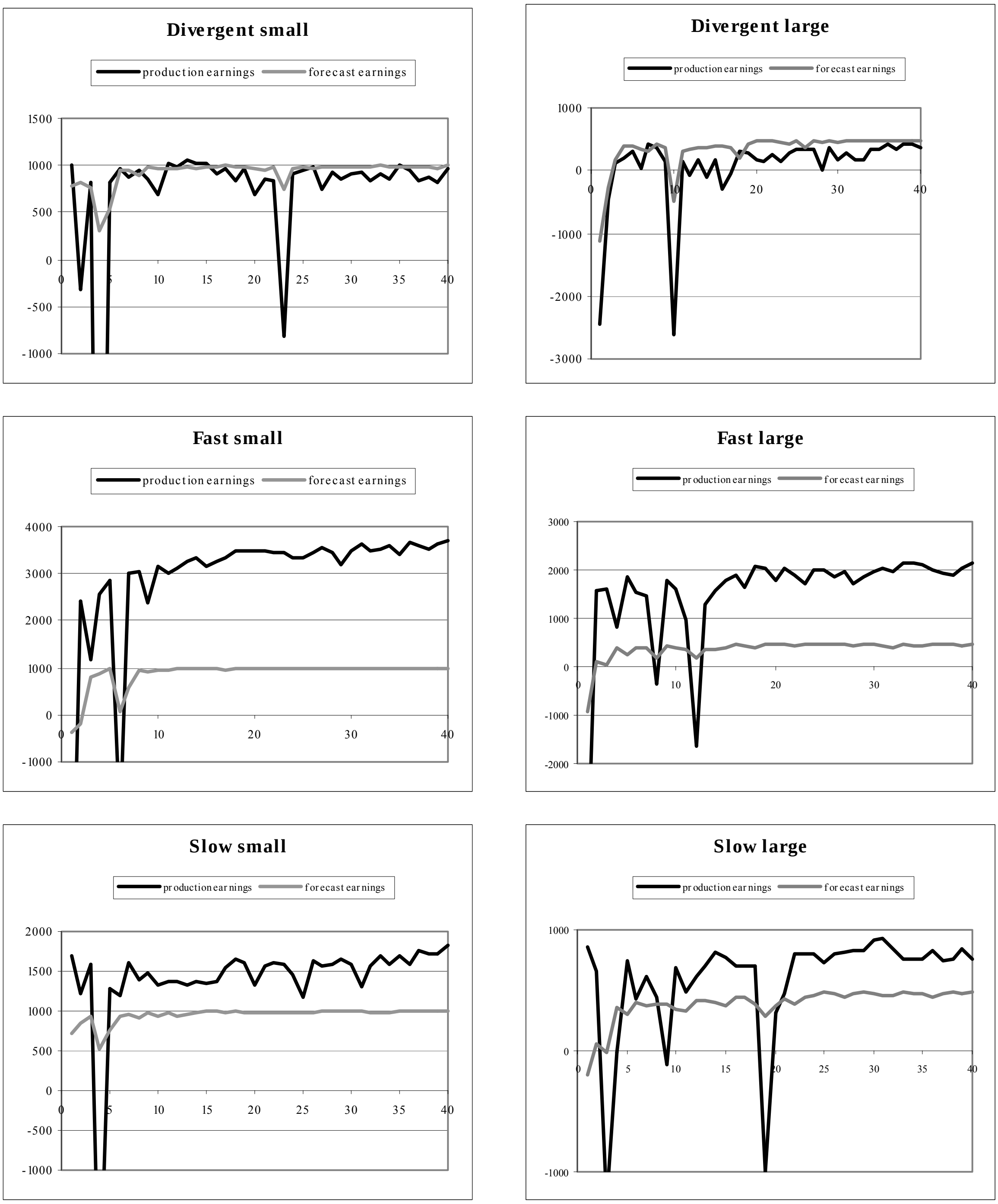



Figure 6.2.Output and forecast average earnings evolution

**Synthesis and main results on profits**

The analysis of production and forecasts earnings allowed us to state on several important results, briefly reminded here:

***Result 1:* For all treatments and each type of decision, in general, with time, subjects become more and more efficient, coordinated and exhibit similar behaviours (average earnings increase while standard deviations decrease). Meanwhile, forecast earnings evolution is smoother.**

***Result 2:* In small groups, subjects are better forecasters, but they have significant higher learning potential in large groups, i.e. all types of agents are asymptotical good forecasters.**

***Result 3:* Divergent groups exhibit some coordination, not expected, and learning, contradicting for the moment the eductive hypothesis.**

### 6.3.2. Prices

The REE price is at 60 points/unit in all treatments. We present in table 6.9 the average market price and the standard deviations calculated for each group, and each treatment.
According to table 6.9 there are few differences in average realized prices between groups and across treatments. Average prices do not differ much between small and large groups. However, since market prices could only take values in multiples of 5, in most cases the average market price is only 1 or 2 steps away from the REE equilibrium. Notice however that all average prices are above the REE price, which is equal to 60, in small groups and in almost all large groups. Therefore there is a tendency for subjects to choose output levels below the equilibrium level. This implies that prices will converge to the REE state from above, confirming an institution effect - our design is close to PO markets, where average price are at or above the Nash range (Holt, 1993), but not surplus analyses (Smith, 1962): in DA markets, if producers surplus exceeds consumers surplus (the case in our *convergent* theoretical design), price tends to converge to the competitive level from below and from above if the reverse situation). But as Holt pointed out, institution effect is always more important than surplus effect.

| Group | | | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|---|
| *Small* | fast | average | 68.8 | 70.3 | 65.3 | 63.8 | 61.3 | 61.8 |
| | | *SD* | *15.8* | *4.4* | *5.8* | *3.7* | *3.8* | *2.9* |
| | slow | average | 60.6 | 69.6 | 59.6 | 66.8 | 68.3 | 69.8 |
| | | *SD* | *2.5* | *3.3* | *9.2* | *6.8* | *4.4* | *2.5* |
| | divergent | average | 70.5 | 68.6 | 63.6 | 71.2 | 67.8 | 64.1 |
| | | *SD* | *3.8* | *6.6* | *12.2* | *19.7* | *4.1* | *4.1* |
| *Large* | fast | average | 61.6 | 59.37 | | | | |
| | | *SD* | *8.7* | *6.5* | | | | |
| | slow | average | 68.3 | 59.6 | | | | |
| | | *SD* | *4.6* | *9.1* | | | | |
| | divergent | average | 61 | 66.1 | | | | |
| | | *SD* | *9.3* | *8.5* | | | | |

Table 6.9. Average market price (and standard deviation) per treatment and per group

**Estimation of the asymptotic convergence point**

Figure 6.3 plots the price dynamics per group for each treatment. In all cases there is a clear convergence towards a price that is slightly above the REE price. Furthermore, deviations occur more frequently in early periods than in late periods. The convergence result is supported by unit root tests (see Appendix). All market price series are level stationary(*I(0)*)[8]. This result clearly shows that price not only converge, but also remain at the convergence level in all markets, supporting coordination and confirming empirically the stability of the equilibrium (when producers have reach the equilibrium level, they remain at the global production level leading to this equilibrium point). Therefore we can estimate the level of convergence, i.e. the value driving the convergence. In order to estimate the asymptotic convergence point of the price level, we apply the method suggested by Noussair and al. (1995) allowing to answer the question about the direction of convergence. In order to do so, for every group price series we run the following regression:

[8] A series is defined as weakly stationary if it has a finite mean, finite variance and finite covariance, all of which are independent of time. With standard notations ($p$ stands for the market price), this means that: $\forall t, E(p_t) = \mu$ (constant), $Var(p_t) = \sigma^2$ (constant), $cov(p_t, p_{t+h}) = \gamma(h)$. The ADF test consists in running a regression of the first difference of the series against the series lagged once, lagged difference terms, and optionally, a constant and a time trend: $\Delta X_t = \alpha + \gamma X_{t-1} + \beta_1 \Delta X_{t-1} + \ldots + \beta_h \Delta X_{t-h} + u_t$. Test stands for ($\gamma$-1) = 0. A large negative $t$-statistic rejects the hypothesis of a unit root and suggests that the series is stationary.

$$p_t = p^{\infty}\frac{(t-1)}{t} + \frac{p^0}{t} + \varepsilon_t\,,$$

where $\varepsilon_t$ is a white noise; $t$ stands for the time variable; $p^{\infty}$ is the asymptote of the dependent variable and $p^0$ is the origin of a possible convergence process. Table 6.10 presents the results for all 24 groups. All variables are significant (*t-test)* and $R^2$ values vary from 0.3 to 0.8 according to the group. We find two main results:

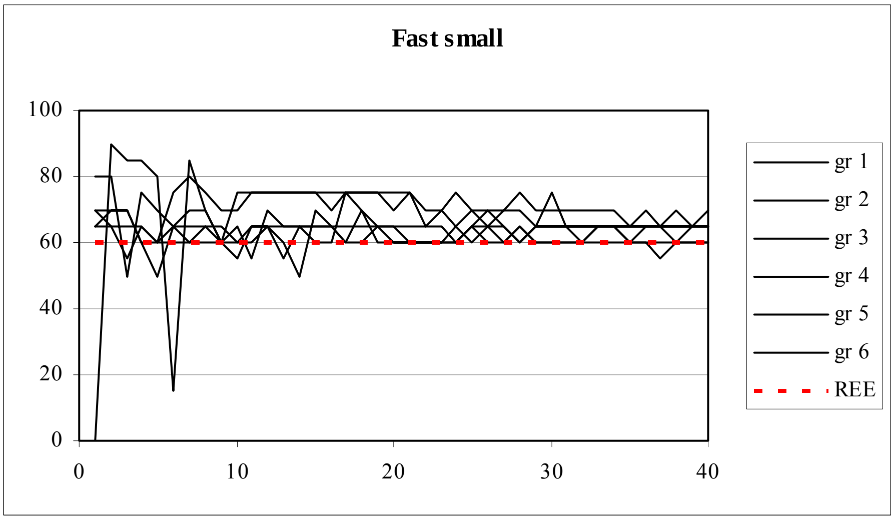
i) there is a convergence point in each treatment (this supports the coordination). On average, the convergence point is at the REE or slightly above (1 step away).

ii) at a 5% significance level we cannot reject the hypothesis of equals asymptotes ($p^{\infty}$) for all groups and all treatments. That means that the ultimate point of convergence is the same between groups. The similarity of the convergence points is independent of the origin of the convergence process: prices starting at a low level (for example at 24.5, as in one large divergent group) as well as over-evaluated prices (for example 87.2 as in one slow large group) are driven in the same neighbourhood of the REE.

| | | fast | | | | slow | | | | divergent | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *small* | | *large* | | *small* | | *large* | | *small* | | *large* | |
| | | $p^0$ | $\boldsymbol{p^{\infty}}$ | $p^0$ | $\boldsymbol{p^{\infty}}$ | $p^0$ | $\boldsymbol{p^{\infty}}$ | $p^0$ | $\boldsymbol{p^{\infty}}$ | $p^0$ | $\boldsymbol{p^{\infty}}$ | $p^0$ | $\boldsymbol{p^{\infty}}$ |
| *group* | *gr1* | 30.7 | **73.4** | 24.3 | **66.1** | 58.7 | **60.8** | 87.2 | **66.1** | 79 | **69.4** | 24.5 | **65.3** |
| | *gr2* | 65.7 | **70.9** | 58.7 | **59.5** | 81.1 | **68.2** | 55.2 | **59.1** | 74.3 | **67.6** | 70.1 | **65.6** |
| | *gr3* | 80.1 | **63.6** | | | 64.5 | **59** | | | 50.9 | **65** | | |
| | *gr4* | 69.6 | **63** | | | 90.7 | **63.8** | | | 81.8 | **69.9** | | |
| | *gr5* | 67 | **60.7** | | | 79 | **67** | | | 77.2 | **66.7** | | |
| | *gr6* | 67.4 | **61.2** | | | 78.4 | **68.7** | | | 71.6 | **63.2** | | |
| | *mean* | 63.4 | *65.4* | 56.5 | *62.8* | 75.4 | *64.5* | 71.2 | *62.6* | 72.4 | *66.9* | 47.3 | *65.4* |

Table 6.10. Asymptote ( $p^{\infty}$)and origin ($p^0$) of the convergent process for prices[9]

[9] for $t = 1$, $p_t = p^0$ and $\lim_{t\to\infty} p_t = p^{\infty}$


Fast small
100
80
60
40
20
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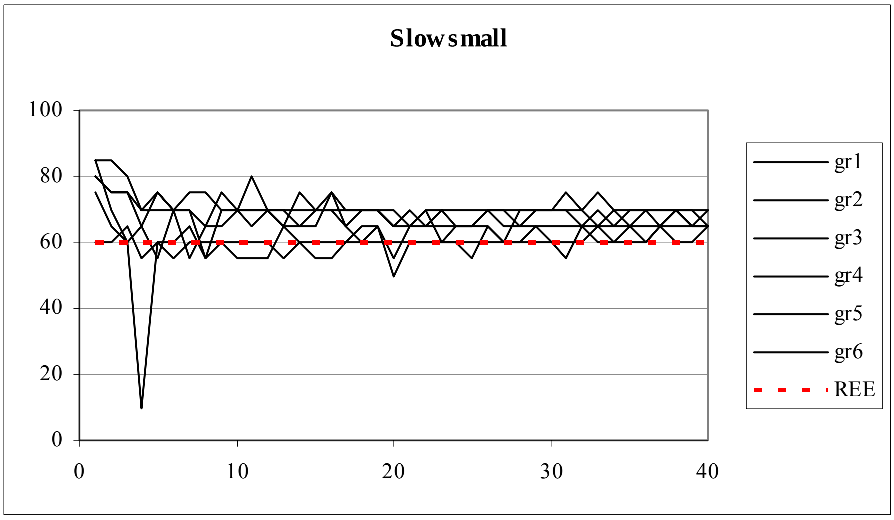
0
10
20
30
40
gr 1
gr 2
gr 3
gr 4
gr 5
gr 6
REE


Slow small
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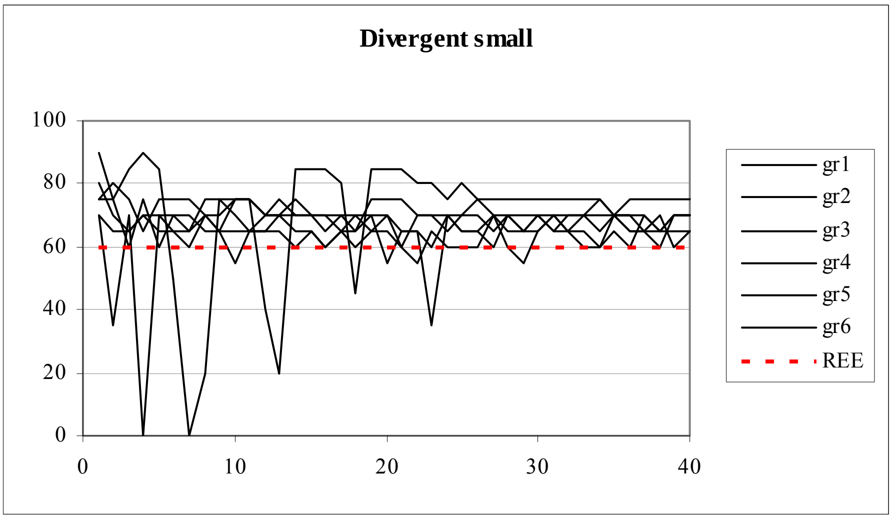
REE


Divergent small
100
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REE

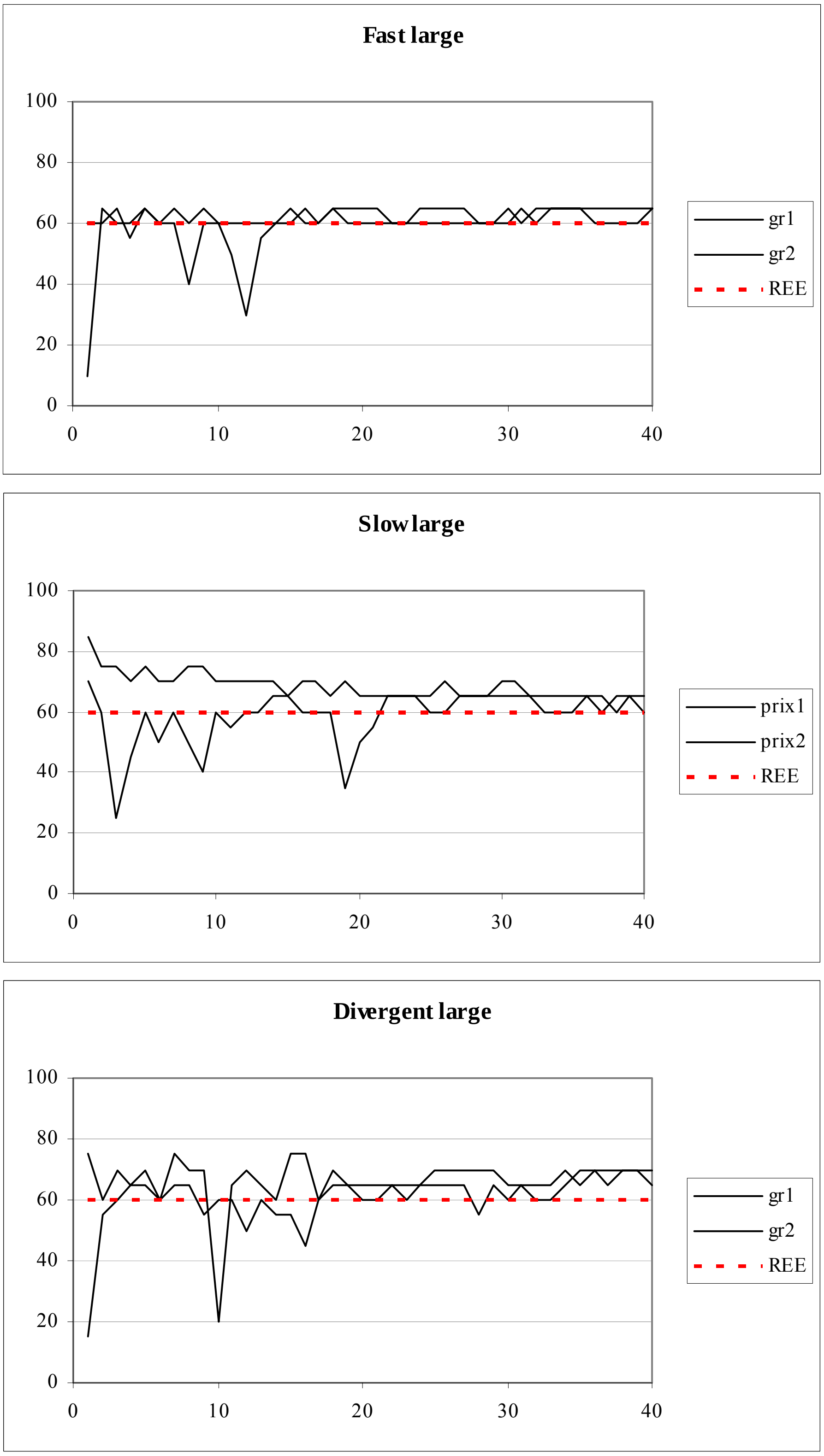



Figure 6.3. Market price evolution per treatment

**The period of convergence**

While prices convergence to a common value and are stationary, convergence might happen more or less early according to groups or treatments: the period when the price enters into a small neighbourhood of the asymptotic value is the period of price stabilisation or convergence. We therefore analyse the period of convergence group by group. We define the convergence period (noted *h*) as the time period when the market price enters into a "restricted price interval" and remains in it until the last period. We call this interval the *interval of convergence* and the corresponding period the *convergence period*. Convergence is thus characterized by two attributes: its type (strong, moderate or weak) and its speed (fast or slow). According to the amplitude of the convergence interval, we shall speak about strong convergence (in a narrow interval) and weak convergence (in a broad interval).

We construct convergence intervals as follows. Let $p_h$ be the market price in period *h* for some group, and let the values $a, b, c, d \in \{0,..100\}$, with $a< b< c< d$, be an ordered sequence of possible price units in the experiment, i.e. multiples of 5. Starting from period *h,* if we observe that the price remains in an interval of two consecutive price units (for example *[c, d],* an amplitude 5 interval) until period 40, we shall speak about *strong convergence*, and we identify *h* as the *convergence period*. The convergence period is the observable counterpart of the *speed of convergence*. With faster convergence, the convergence period will be further away from the end period. If convergence happens in a larger interval (for example *[ b, d ],* an amplitude 10 interval) we shall speak about *weak* convergence. We look for weak convergence (thus on 3 prices on a whole of 21).
Since all the groups, even within the same treatment, do not converge at the same period, we compare the relative periods of convergence and try to see whether we can observe outstanding differences in the speed of convergence.

Table 6.11 presents the speed of convergence for all treatments and all groups. Groups in small treatments do not seem to converge faster than their counterpart in large treatments. Furthermore, treatments for which convergence is "fast" do not converge faster than treatments for which convergence should be slow.[10] Although further investigation is required, these preliminary findings contradict the predictions of the eductive reasoning hypothesis for the *divergent* groups.

[10] Mann-Whitney test ($p>0,05$)

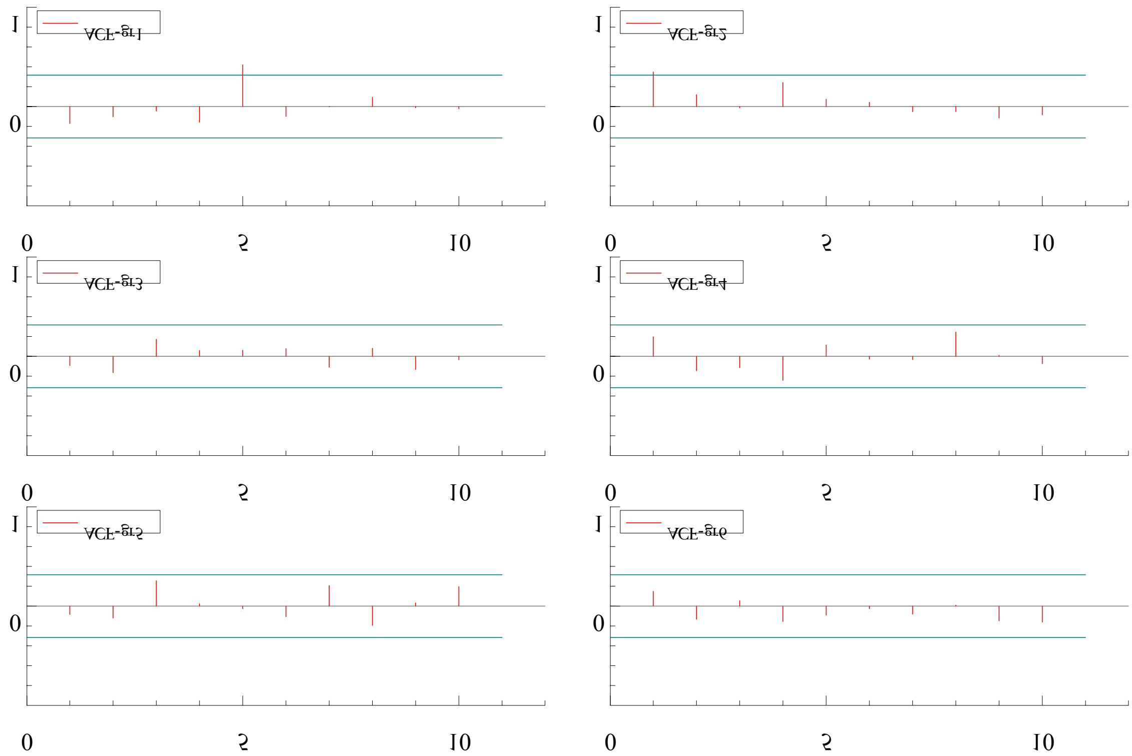
| | | | | | | | |
|---|---|---|---|---|---|---|---|
| ***small*** | *fast* | 2 | 5 | 7 | 9 | 17 | 18 |
| | *slow* | 1 | 2 | 5 | 11 | 20 | 23 |
| | *divergence* | 2 | 9 | 10 | 21 | 23 | 30 |
| ***large*** | *fast* | 2 | 12 | | | | |
| | *slow* | 10 | 21 | | | | |
| | *divergence* | 15 | 17 | | | | |

Table 6.11. Convergence periods for the market price

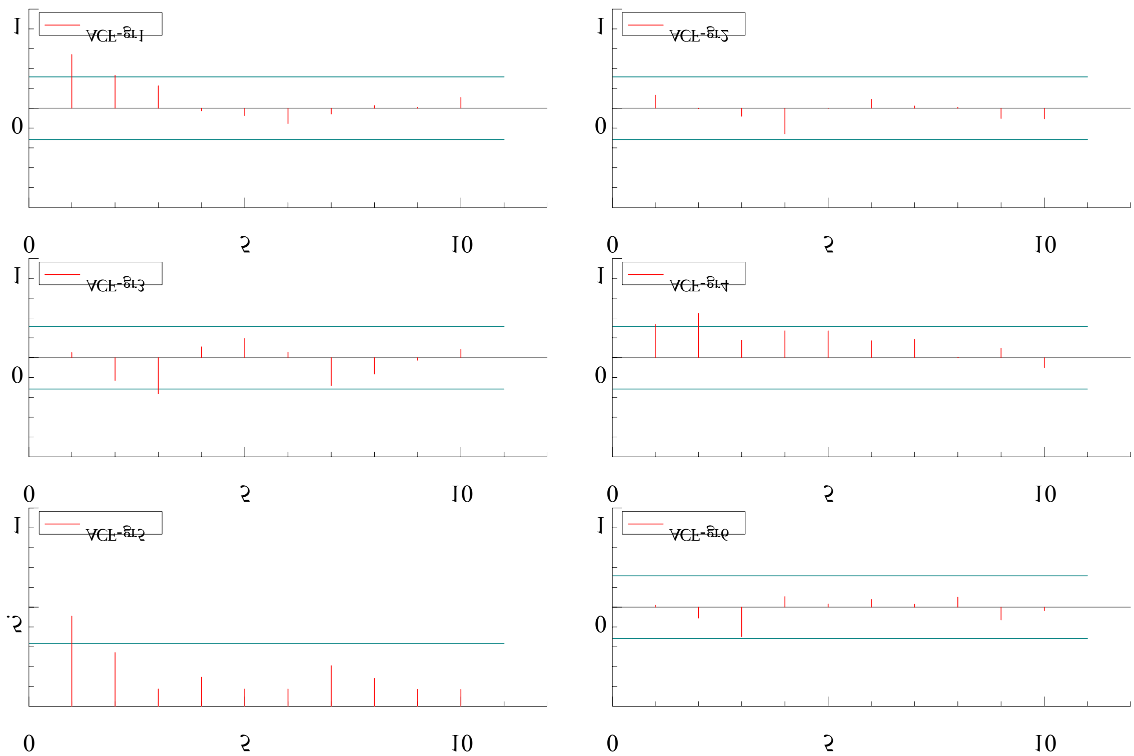
**Predictability of prices**

Price series are stationary and asymptotically converge to a common value and, starting from the point of convergence, exhibit little volatility. These characteristics describe *in mean* the behaviour of RE convergent series. To get a further insight, we investigated the forecastability characteristics of the market price series. Do these series incorporate a trend or structure that could help subjects to forecast the price for the next period and to correlate their production decisions with that forecast in order to perform better? The simplest way to make use of past values a take a production decision is to make a linear inference on these values. Therefore, to answer that question we analyse for each group and each treatment the autocorrelation structure of market prices. If market prices do correspond to RE-convergent series, than they should be truly random series, fluctuating irregularly around a constant mean (REE, i.e. 60), with small and constant variance. The autocorrelation plots are extremely suggestive. Next figure presents the results for all small groups. With few exceptions, there is no price pattern easily exploitable by the subjects. When regressions are conducted with the first 10 lags, very few lags are significant and we cannot observe a regular lag structure.[11]The only treatment in which 3 groups out of 6 exhibit significant positive lags at the beginning of the experiment is the slow treatment.

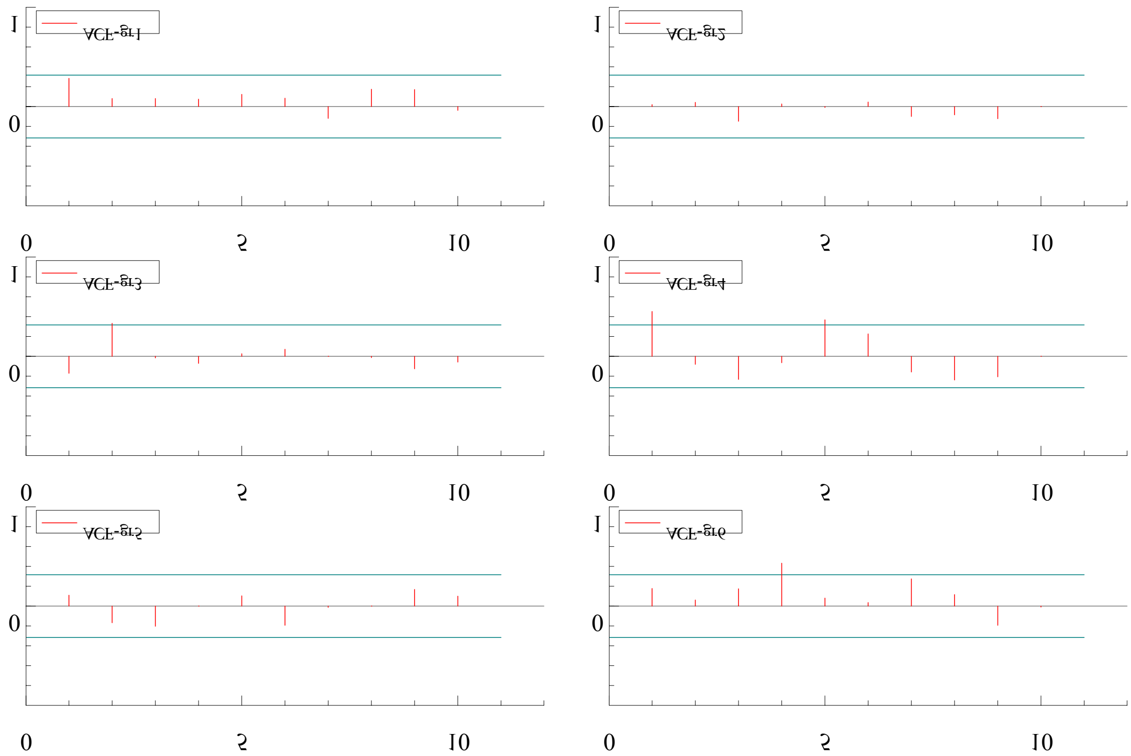
[11] The lines in the plots are the two standard error Barlett bands at 2,5% significance level



(a) fast small



(b) slow small



(c) divergent small

Figure 6.4. Autocorrelations for small groups

Figure 6.5 presents the corresponding graphs for large groups. The same pattern as in some slow small groups is observable in one slow large group.

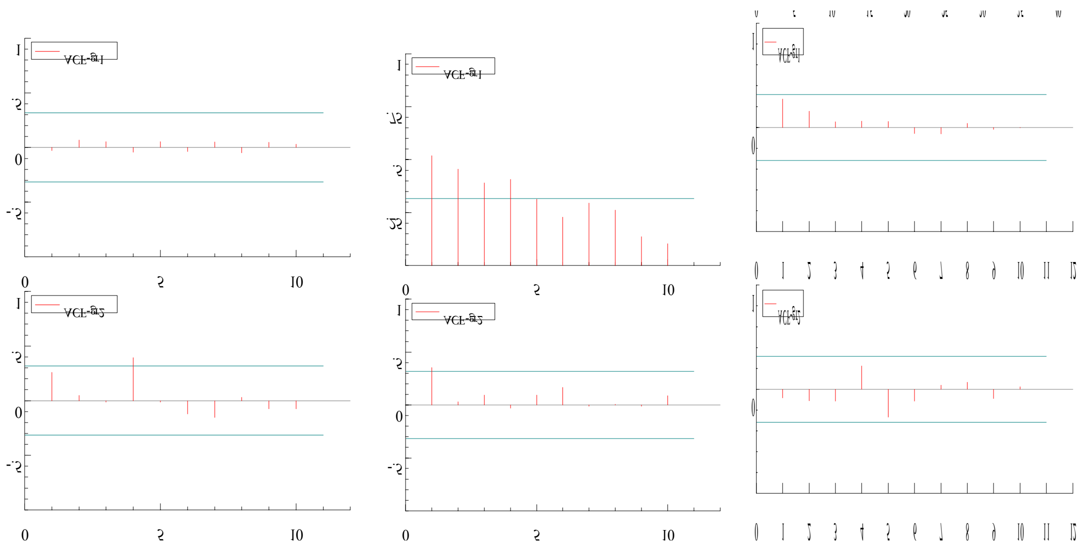


Figure 6.5. Autocorrelations for fast, slow and divergent large groups

**Synthesis and main results on prices**

***Result 1:*** **Market prices series are stationary and asymptotically converge to common values in a close neighbourhood of the REE. No significant difference in the period of convergence exists between small and large groups.**

***Result 2:*** **No easily exploitable pattern for forecastability is found in the structure of the market prices (except for some *slow* groups).**

### 6.3.3. Price forecasts

We analyze in this section the price forecasts. We make two assumptions related to the price predictions. First, these forecasts should converge to the REE as the agents learn the market by an adaptive or eductif reasoning in treatments *fast* and *slow*; this coordination figure was underlined by the tendency of the forecasts profits. It results from this that the forecast errors should be reduced along the time. Second, agents should coordinate their forecasts and their production decisions; therefore, the best-response price induced from their forecast (by automatic computation of the production decision) should correspond to the realized market price.

**Forecasts coordination**

In this section we approach the first assumption, related to the coordination of price forecasts. Price predictions determine a forecast profit or loss, calculated according to the quadratic scoring rule. This rule of calculation is such as the subjects always may find it beneficial to communicate their true beliefs (this was specified in the instructions). Table 6.12 presents the descriptive statistics for the forecasts for all groups in all treatments.

Descriptive statistics do not exhibit significant differences between treatments. As forecasts were rewarded according to their quality, we need some additional qualitative indicators to describe them. As stated before, a good forecast implies a high forecast profit, which corresponds to a small forecast error. Therefore we try to characterize the forecasts by calculating the average individual quadratic forecast error in each group.

| Group | | | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|---|
| *Small* | fast | average | 70.5 | 66 | 71 | 62.5 | 62.3 | 62 |
| | | *SD* | *12* | *5.8* | *6* | *9* | *6* | *4* |
| | slow | average | 60.4 | 58 | 70 | 67 | 70 | 68.5 |
| | | *SD* | *4.6* | *3.8* | *10* | *6* | *5* | *7.2* |
| | divergent | average | 71.1 | 63 | 70.1 | 70 | 67.5 | 63 |
| | | *SD* | *3.44* | *5.12* | *10* | *17* | *5.5* | *8.8* |
| *Large* | fast | average | 62.4 | 59.5 | | | | |
| | | *SD* | *11.89* | *10.28* | | | | |
| | slow | average | 67.3 | 54 | | | | |
| | | *SD* | *8.8* | *12* | | | | |
| | divergent | average | 61 | 67.7 | | | | |
| | | *SD* | *11.5* | *11.7* | | | | |

Table 6.12. Statistics for price forecasts

The forecast error is the distance $\left|p_{it}^{e} - p_t\right|$, thus the average quadratic forecast error is defined by $\frac{1}{TN}\sum_{i=1}^{n}\sum_{t=t_0}^{T}(p_{it}^{e} - p_t)^2$, where $T$ is the number of periods over which we calculate this error, $t_0$ is the initial point of the observation ($T$ can thus go from 1 to 40 as well as $t_0$), $N$ is the number of players ($N$ can go from 1 to 5 or from 1 to 10, according to the group size), $p_{it}^{e}$ is agent's $i$ price forecast in period $t$, and $p_t$ is the realized market price at period $t$ (the same for all the agents within a group). As we consider the 10 first periods in an experiment as a "phase of entry", we can calculate this average error on the last 30 periods of the experiment. This average individual quadratic forecast error can be broken into the following terms (Hommes, 2002):

$$\frac{1}{TN}\sum_{i=1}^{n}\sum_{t=t_0}^{T}(p_{it}^{e} - p_t)^2 = \frac{1}{TN}\sum_{i=1}^{n}\sum_{t=t_0}^{T}(p_{it}^{e} - \overline{p_t^{e}})^2 + \frac{1}{T}\sum_{t=t_0}^{T}(\overline{p_t^{e}} - p_t)^2,$$

where $\overline{p_t^{e}} = \frac{1}{n}\sum_{i=1}^{n}p_{it}^{e}$ is the average price forecast in a $N$-subjects group for period $t$. The first term, $\frac{1}{TN}\sum_{i=1}^{n}\sum_{t=t_0}^{T}(p_{it}^{e} - \overline{p_t^{e}})^2$, is the average quadratic dispersion error, i.e. it measures the discrepancy between the individual forecasts. It gives the quadratic average of the distance between the individual forecasts and the average forecast of a group, calculated for all the periods and all the agents, i.e. the relative position of an individual forecast to the average forecast in his group. This error can be null if and only if all the participants make exactly the same price forecast. If this term is close to 0 or small, the differences between the individual predictions and the mean forecast are weak and we can consider that the agents use the same price prediction strategies. The term $\frac{1}{T}\sum_{t=t_0}^{T}(\overline{p_t^e} - p_t)^2$ measures the quadratic error between the average forecast in a group and the realized market price. Van de Velden (2001) calls the term $\left|\overline{p}_t^e - p_t\right|$ the "lead" error, because it measures how on average the predicted price leads the realized price. This term is common to all individuals in a group. Therefore, we call the term $\frac{1}{T}\sum_{t=t_0}^{T}(\overline{p_t^e} - p_t)^2$ the quadratic average common error. If individual forecasts are close to the market price *on average*, this term should be relatively small. This assumption is in conformity with Muth (1961) assumption on rational expectations, allowing the distribution of anticipations to approach the theoretical prediction, i.e. individual anticipations can be false, but at the aggregate level anticipations are roughly correct. We calculate all these terms for all the groups and all the treatments for the 30 last periods only, because of the disturbing character of the first 10 periods (we aimed to avoid in these calculations the variations in predictions and prices due to participants trying to learn how to forecast accurately). Table 6.13 presents this decomposition for *small* treatments.

| | | *Average individual error* | *Average dispersion error* | | *Average common error* | |
|---|---|---|---|---|---|---|
| Div | group | $\frac{1}{TN}\sum_{i=1}^{n}\sum_{t=t_0}^{T}(p_{it}^e - p_t)^2$ | $\frac{1}{TN}\sum_{i=1}^{n}\sum_{t=t_0}^{T}(p_{it}^e - \overline{p_t^e})^2$ | | $\frac{1}{T}\sum_{t=t_0}^{T}(\overline{p_t^e} - p_t)^2$ | |
| *T=30* | 1 | 13.33 | 4 | *(30%)* | 9.33 | *(70%)* |
| *$t_0$=11* | 2 | 51.66 | 14.13 | *(27%)* | 37.53 | *(73%)* |
| | 3 | 36.16 | 14 | *(39%)* | 22.16 | *(61%)* |
| | 4 | 254 | 106 | *(41%)* | 148 | *(58%)* |
| | 5 | 18 | 6 | *(33%)* | 12 | *(66%)* |
| | 6 | 61 | 33 | *(54%)* | 28 | *(45%)* |

| Fast | group | Average individual error $\frac{1}{TN}\sum_{i=1}^{n}\sum_{t=t_0}^{T}(p_{it}^e - p_t)^2$ | Average dispersion error $\frac{1}{TN}\sum_{i=1}^{n}\sum_{t=t_0}^{T}(p_{it}^e - \overline{p_t^e})^2$ | | Average common error $\frac{1}{T}\sum_{t=t_0}^{T}(\overline{p_t^e} - p_t)^2$ | |
|---|---|---|---|---|---|---|
| *T=30* | 1 | 8.16 | 3.53 | *(43%)* | 4.63 | *(57%)* |
| $t_0$*=11* | 2 | 19.66 | 6.73 | *(34%)* | 12.93 | *(66%)* |
| | 3 | 19.16 | 8.8 | *(46%)* | 10.36 | *(53%)* |
| | 4 | 51 | 40 | *(80%)* | 11 | *(20%)* |
| | 5 | 36 | 22 | *(74%)* | 13 | *(26%)* |
| | 6 | 13 | 6 | *(48%)* | 7 | *(52%)* |

| Slow | group | Average individual error $\frac{1}{TN}\sum_{i=1}^{n}\sum_{t=t_0}^{T}(p_{it}^e - p_t)^2$ | Average dispersion error $\frac{1}{TN}\sum_{i=1}^{n}\sum_{t=t_0}^{T}(p_{it}^e - \overline{p_t^e})^2$ | | Average common error $\frac{1}{T}\sum_{t=t_0}^{T}(\overline{p_t^e} - p_t)^2$ | |
|---|---|---|---|---|---|---|
| *T=30* | 1 | 6 .33 | 3.46 | *(55%)* | 2.86 | *(45%)* |
| $t_0$*=11* | 2 | 8.66 | 2.2 | *(25%)* | 6.46 | *(75%)* |
| | 3 | 43.5 | 29 | *(67%)* | 14.5 | *(33%)* |
| | 4 | 24 | 8 | *(33%)* | 16 | *(66%)* |
| | 5 | 12 | 4 | *(33%)* | 7 | *(66%)* |
| | 6 | 24 | 17 | *(70%)* | 7 | *(30%)* |

Table 6.13. Errors decomposition in small groups

The errors due to the dispersion of forecasts are weaker than the common errors in 13 cases out of 18. This result indicates coordination on a common price forecast strategy. The fact that the highest relative part of the quadratic average forecast error is due to the common errors (systematic difference between the anticipated average price and the real price) implies a rejection of the hypothesis supposing that the agents could retain, when they make forecasts for prices, the rule of rational anticipations with errors as a strategy. This result suggests that the errors of the agents are correlated: the agents make forecast errors and this in the same direction. An interrogation rises from this analysis: are forecast errors structural? Before answering this question, we will have a look at errors decomposition in large groups, presented in the next table.

Contrary to small groups, in large groups dispersion errors are higher than common errors in all treatments. This result can be interpreted as coordination *in mean*: within a group, participants don't have very similar forecasts, but on average, they are able to hit the market price.

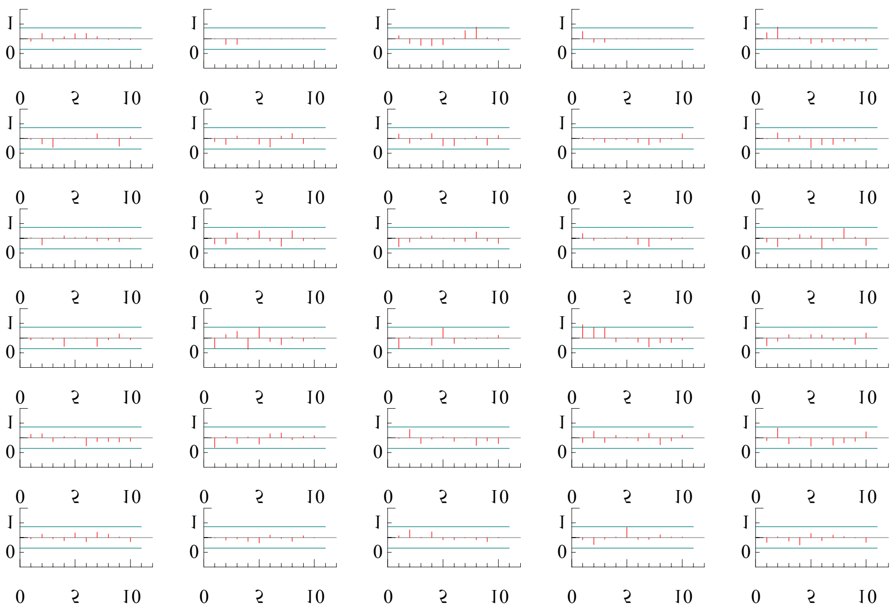
| Fast | group | Average individual error $\frac{1}{TN}\sum_{i=1}^{n}\sum_{t=t_0}^{T}(p_{it}^e - p_t)^2$ | Average dispersion error $\frac{1}{TN}\sum_{i=1}^{n}\sum_{t=t_0}^{T}(p_{it}^e - \overline{p_t^e})^2$ | | Average common error $\frac{1}{T}\sum_{t=t_0}^{T}(\overline{p_t^e} - p_t)^2$ | |
|---|---|---|---|---|---|---|
| *T=30* | 1 | 88.9 | 75. 6 | *(85%)* | 13.3 | *(15%)* |
| $t_0$*=11* | 2 | 95.2 | 50 | *(52%)* | 45.2 | *(48%)* |

| Slow | group | Average individual error $\frac{1}{TN}\sum_{i=1}^{n}\sum_{t=t_0}^{T}(p_{it}^e - p_t)^2$ | Average dispersion error $\frac{1}{TN}\sum_{i=1}^{n}\sum_{t=t_0}^{T}(p_{it}^e - \overline{p_t^e})^2$ | | Average common error $\frac{1}{T}\sum_{t=t_0}^{T}(\overline{p_t^e} - p_t)^2$ | |
|---|---|---|---|---|---|---|
| *T=30* | 1 | 49.2 | 43.8 | *(89%)* | 5.3 | *(11%)* |
| *$t_0$=11* | 2 | 110.8 | 56.5 | *(51%)* | 54.3 | *(49%)* |

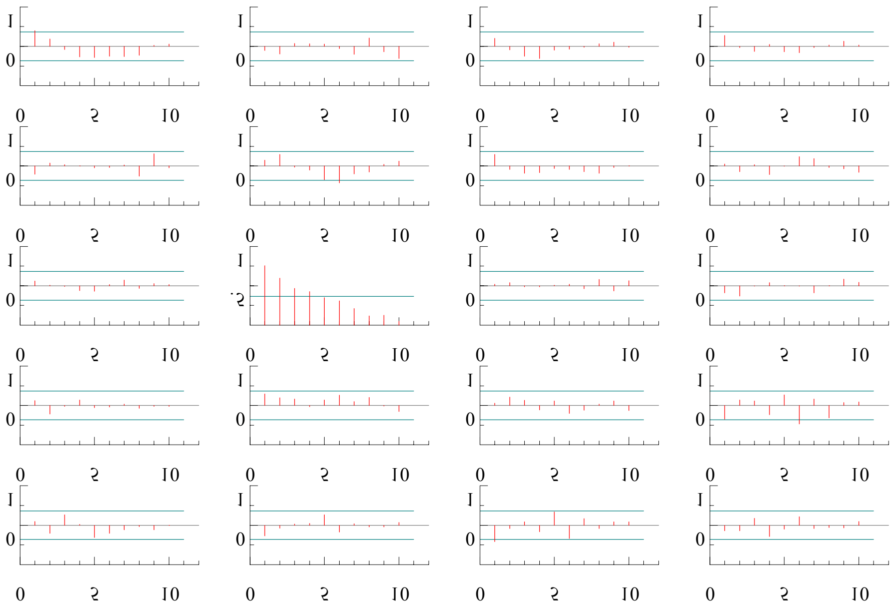
| Div | group | Average individual error $\frac{1}{TN}\sum_{i=1}^{n}\sum_{t=t_0}^{T}(p_{it}^e - p_t)^2$ | Average dispersion error $\frac{1}{TN}\sum_{i=1}^{n}\sum_{t=t_0}^{T}(p_{it}^e - \overline{p_t^e})^2$ | | Average common error $\frac{1}{T}\sum_{t=t_0}^{T}(\overline{p_t^e} - p_t)^2$ | |
|---|---|---|---|---|---|---|
| *T=30* | 1 | 73.8 | 47.5 | *(64%)* | 26.3 | *(36%)* |
| *$t_0$=11* | 2 | 99 | 75.4 | *(76%)* | 23.6 | *(24%)* |

Table 6.14. Error decomposition for large groups

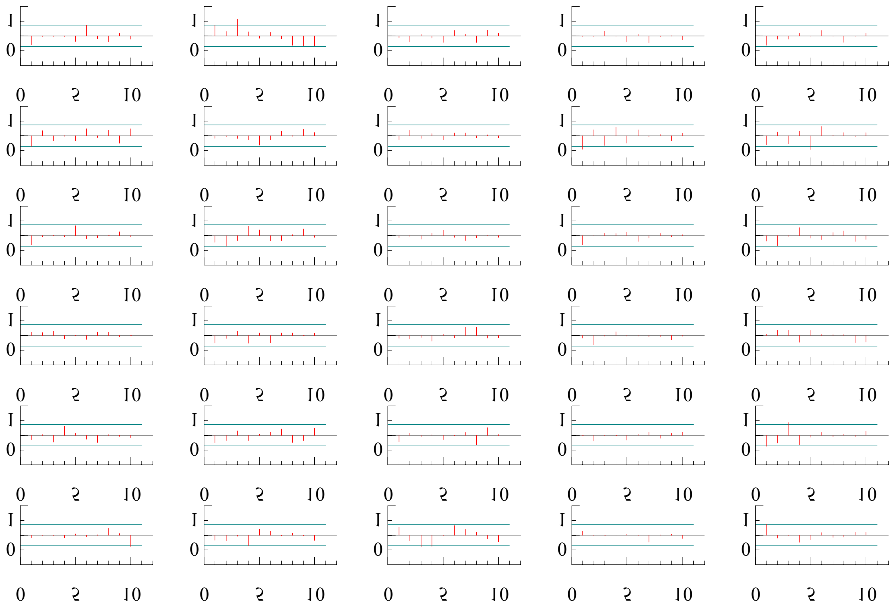
As in all treatments and all groups we find positive forecast errors, previous tables indicate that most of the participants make structural errors; however, the assumption of rationality should imply that these errors are not correlated with the available information, i.e., among other elements, with the past realization of market prices. In order to test this implication, we compute, for each participant, the analysis of its forecasts errors: we draw the autocorrelation function of the time series of forecast errors $p_t - p_t^e$, only on the same last 30 periods on which we previously calculated the forecast errors. Autocorrelation graphs for the forecast errors are presented below.



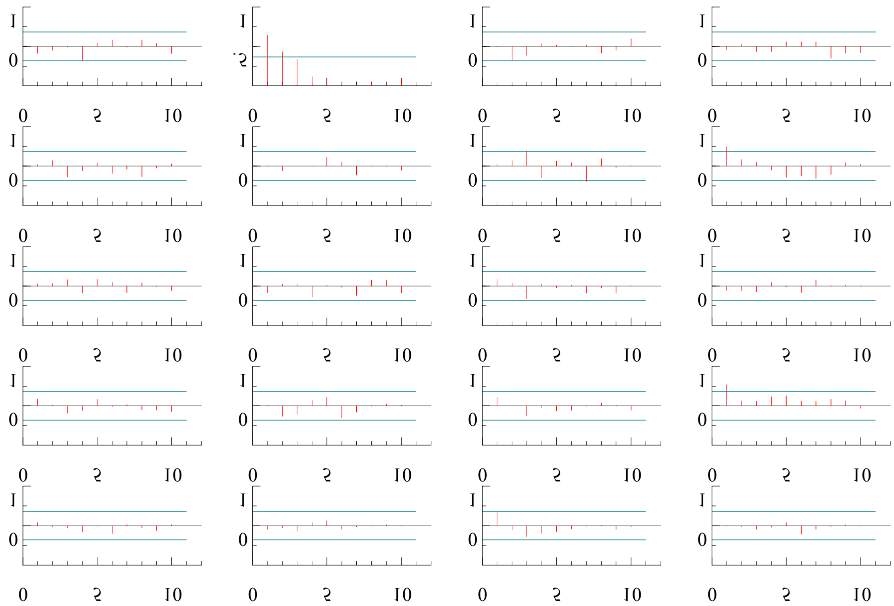
(a) small slow



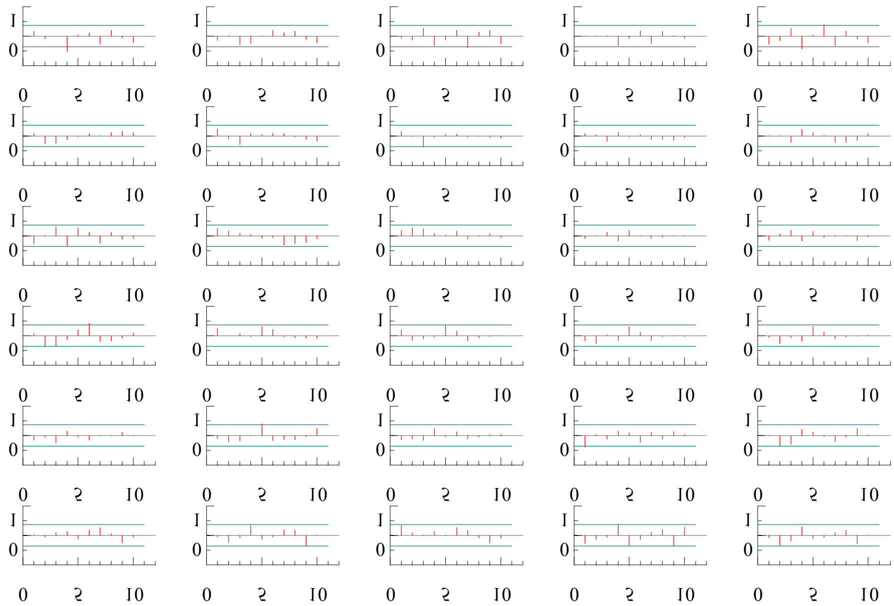
(b) slow large



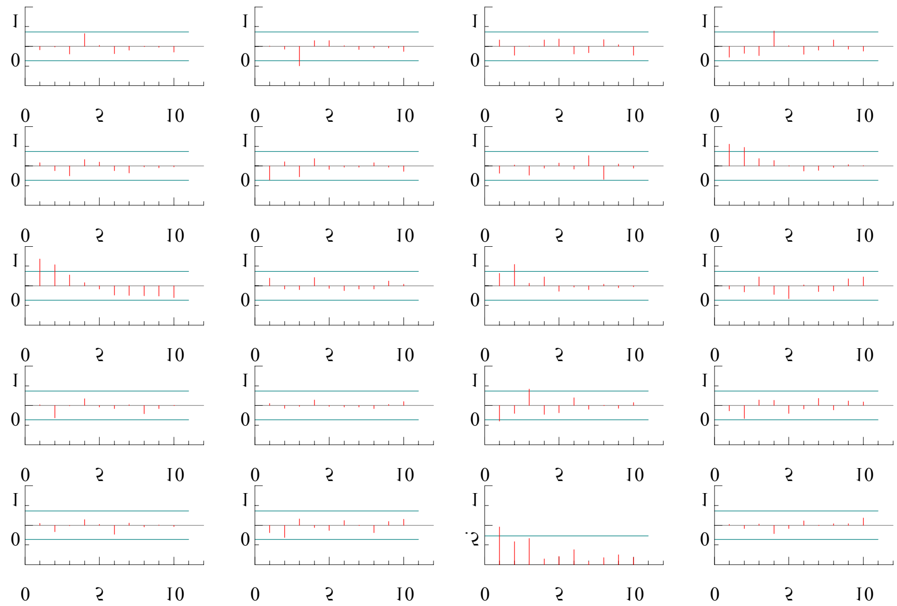
(c) fast small



(d) fast large



(e) divergent small



(f) divergent large

Figure 6.6. Autocorrelations plots for forecast errors.

About ⅓ of the participants in small groups exhibit some significant lags (out of the five first), compared to only ¼ in large groups.

**A measure of predictive success**

To have a look at the convergence process we calculate the measure of predictive success of Selten (1983). This measure is defined as the difference between the relative frequency of results compatible with the theoretical prediction and the relative size of the prediction area:

$$m = r - a,$$

where $m$ is the measure of predictive success, $r$ is the relative frequency of results compatible with the theory and $a$ is the relative size of the prediction zone. We calculate a broad measure of predictive success here (i.e. predicting in a stable interval and around the market price). The areas of prediction are the intervals of convergence, of an amplitude of 10 (thus include 3 prices out of 21) and thus $a$ = 14%. We calculate the frequencies of success for each treatment ($r$) by counting the number of differences $\left|p_t - p_t^e\right| \leq 10$ and reporting it to the total number of predictions in the treatment. Table 6.15 presents these results and $m$ for all the treatments. Over 65% of forecast are successful.

| | *fast small* | *fast large* | *slow small* | *slow large* | *div small* | *div large* |
|---|---|---|---|---|---|---|
| *r* | 91.25% | 88.75% | 94.5% | 82.5% | 92.33% | 83.75% |
| *a* | 14% | 14% | 14% | 14% | 14% | 14% |
| *m* | *77.25%* | *74.75%* | *80.5%* | *68.5%* | *78.33%* | *69.75%* |

Table 6.15. A measure of predictive success for forecasts

**Adjustment process due to individual experience**

In this experiment, participants have to take two decisions and they can earn money from each one. Their guess about the market price is rewarded according to its quality: as $\Pi_{ft} = F - 0.8 \times (p^e{}_t - p_t)^2$, they earn $F$ if the forecast is perfect, i.e. $p^e{}_t = p_t$, and they are penalized if $\left| p_t^e - p_t \right| \neq 0$. We suppose that a participant is always willing to improve his earnings, i.e. to reach $F$ as a payment for his forecast. If it is the case, it is because either they have predicted more than the realized price and at the next period they should reduce their forecast, either they have predicted less, and they should increase the value of their prediction. Thus participants have to adjust their forecasts until they reach the optimum direction which allows them to hit the exact market price. Following Nagel (1995), we suppose that the guessing process starts at some initial reference point and define the adjustment factor in a period by measuring the deviations in predictions from the realized price in the previous period:

$$a_{it} = \begin{cases} \dfrac{p_{it}^e}{I}, \; t = 1, \; I \text{ is the initial reference point} \\ \\ \dfrac{p_{it}^e}{p_{t-1}}, \; t > 1 \end{cases}$$

If the forecast payment of a participant is smaller than $F$, it means that the he adjusted more (less) than the retrospective "optimal" adjustment factor in period $t$, simply defined as the optimal deviation from the realized price in period $t$-1 that leads to the realized price in period $t$: $a_t^{opt} = \dfrac{p_t}{p_{t-1}}$. The idea underling this learning direction theory described by Nagel (1995) for guessing games is that in an *ex post* reasoning process a player compares his adjustment factor $a_t^i$ with the optimal factor $a_{opt}$. If they differ, in the next period he most likely adapts in the direction of the optimal adjustment factor. Thus, he reflects what deviation from the previous initial reference point would have been better:

$$\text{if } a_{it} > a_t^{opt} \rightarrow a_{it+1} < a_t$$

$$\text{if } a_{it} < a_t^{opt} \rightarrow a_{it+1} > a_t$$

i.e., if he observed that his forecast was above the realized market price in the previous period (his adjustment factor was higher than the optimal adjustment factor), then he should decrease his rate; if his prediction was below the realized market price (the adjustment factor was lower than the optimal adjustment factor), he should increase his adjustment factor. Table 6.16 shows the changes of behaviour due to experience, pooled over all subjects and all periods within a treatment. The first observation is that between 32.5% and 50.4% of the participants adjust at exactly the optimal factor. This population is constituted of the participants listed in the middle of table 6.16. ($a_{it}=a_t^{opt}$). The lower rate stands for the large divergent treatment, and the higher for the slow small treatment. Confirming earlier results, within a type of convergence, these rates are always higher in small groups than in large groups (the differences between fast, slow and divergent small groups and the corresponding large groups are in the range of 8-10%). These subjects thus earn the maximum profit from the forecast activity. More than half of them are time-consistent (in the table they are marked with an asterisk), i.e. if they adjusted at the optimal factor in period *t*, they keep being perfect forecasters in period *t*+1. Therefore, for the analysis of the learning direction theory we will only focus on the remaining subjects for which there are still possibilities of forecast profits improvement (supposed to try to improve their earnings and are located in the first ($a_{it}< a_t^{opt}$) and last ($a_{it}> a_t^{opt}$) sections of table 6.16: for these subjects the adjustment is not optimal and they are almost equally spilt between over and under-adjusters.

On average only 30% of the participants who underestimated the adjustment factor in period *t* act in the direction of the simple theory proposed by Nagel (1995)[12]. The percentages are significantly higher in large treatments than in small ones in fast and slow cases. The opposite situation occurs in the case when participants adjusted higher than the optimal factor in period *t* (last line in table). They behave in the direction of the theory in less than 30% of the situations (except for the small divergent treatment) and they mostly continue over-adjusting. In both cases the proportion of an adjustment at exactly the optimal factor in period *t*+1 (following an over or an under-adjustment in period *t*) is about 30%. In fact, the null

[12] These participants are marked with an asterisk in the table, first line.

hypothesis of an equal split in behaviour after an over or an under-adjustment in period $t$ cannot be rejected. These results do not confirm the learning direction theory at the same extent as those provided by Nagel (1995), who find a proportion of 73% of choices consistent with the theory on average in the BCG+.

| | *fast* | | *slow* | | *divergent* | |
|---|---|---|---|---|---|---|
| | *small* | *large* | *small* | *large* | *small* | *large* |
| $a_{it} < a_t^{opt}$ et $a_{it+1} > a_{it}$ | 6.7%* | 11%* | 8%* | 13%* | 10.5%* | 9.6%* |
| $a_{it} < a_t^{opt}$ et $a_{it+1} = a_{it}$ | 11.6% | 8.7% | 6% | 9.3% | 6% | 9.1% |
| $a_{it} < a_t^{opt}$ et $a_{it+1} < a_{it}$ | 6% | 13.8% | 9% | 10.5% | 9% | 15.2% |
| $a_{it} = a_t^{opt}$ et $a_{it+1} > a_{it}$ | 9% | 9.2% | 10% | 10% | 12% | 8% |
| $a_{it} = a_t^{opt}$ et $a_{it+1} = a_{it}$ | 27.9%* | 23.7%* | 29.4%* | 26.1%* | 19.65%* | 17.6%* |
| $a_{it} = a_t^{opt}$ et $a_{it+1} < a_{it}$ | 12% | 8.7% | 11% | 6.5% | 10% | 6.9% |
| $a_{it} > a_t^{opt}$ et $a_{it+1} > a_{it}$ | 12% | 13.4 % | 12% | 11.5% | 8.1% | 15.7% |
| $a_{it} > a_t^{opt}$ et $a_{it+1} = a_{it}$ | 7% | 6.4% | 6.6% | 9.2% | 7.8% | 8.8% |
| $a_{it} > a_t^{opt}$ et $a_{it+1} < a_{it}$ | 7.8%* | 5.1%* | 8%* | 3.9%* | 17%* | 9.1%* |

Table 6.16. Relative frequencies of changes in adjustment factors due to individual experience in the preceding period.

About 31% of the total number of participants over- adjust after an suboptimal profit and this proportion is slightly higher than the percentage of under-adjusters (28%). We thus identify a tendency for overreaction that we will investigate in further sections (in order to try to confirm/infirm it in production decisions). This analysis depicted results about the relative value of the adjustment factor; before closing the inspection of forecasts, we will have a look at the absolute value of $a_{it}$. Absolute value will indicate us the exact type of adjustment that participants put into practice in their forecasts and will provide us a classification of individual subjects into several expectation schemes. For example, if $a_{it}$=1, participants just copy the last realized market price when announcing their price prediction, i.e. they perform a naïve adjustment or hold naïve expectations. For each subject in each period, one general way to express forecast as a function of past expectations and pas prices is:

$$p_t^e = p_{t-1}^e + w_t\,(p_{t-1} - p_{t-1}^e),$$

where $w_t$ is an (unique) adaptive factor. The last equation can also be rewritten and transcripted in terms of the adjustment factors that we analysed earlier as:

$$w_t = \frac{p_t^e - p_{t-1}^e}{p_{t-1} - p_{t-1}^e} = \frac{a_t - \dfrac{a_{t-1}}{a_{t-1}^{opt}}}{1 - \dfrac{a_{t-1}}{a_{t-1}^{opt}}},$$

with usual notations. Therefore, an adjustment factor equal to the optimal one gives us a null denominator and an infinite $w_t$, corresponding to the case of perfect forecasts; $a_t = 1$ ($w_t = 1$) stands for naïve expectations; $w_t = 0$ for immobilism; a small $a_t < 1$ for adaptive expectations etc. Looking for a forecast rule in similar experiments, Hommes (1999) reports between 15% and 30% of adaptive players. We perform calculations for our experiments and report them as frequencies of $w$ values over time in table 6.17.

Our percentage of adaptive players is much smaller than in Hommes(1999): as Hommes classifies as adaptive players all subjects for which $w$ is small ($-0.1 \le w \le 0.3$), it includes subjects who stick to a forecast ($w = 0$) in this category. In spite of full information about the market, table 6.17 indicates that almost 20% of our players behave naively ($w = 1$) and between 20 and 25% of the participants stick to a forecast ($w = 0$), believing that his predicted price will end up by prevailing on the market. Perfect forecasters represent between 30 and 50% of the participants ($w = \infty$) and these percentages confirm our previous results: relatively more participants are perfect forecasters in small groups. The percentage of perfect forecasters exhibits the most significant difference with Hommes, who only find rare cases with $p_{t-1} = p_{t-1}^e$. We believe that this difference could simply be attributed to the fact that subjects had no information about the underlying market equations in Hommes(1999), whereas in our experiment they posses symmetric full (exogenous) information. At the inspection of the remaining 10-20% of the participants who do not belong to classes $w = 0$, $w = 1$ or $w = \infty$, we do not find support for Markov switching[13], therefore we include these subjects in a category where no simple rule or no rule at all is observable (frequency distributions are irregular).

[13] Following Hommes(1999), Markov switching corresponds to $-0.1 \le w \le 0.1$ for at least 1/3 of the periods and $0.9 \le w \le 1.1$ for at least 2/3 of the periods.

| | *fast* | | *slow* | | *divergent* | |
|---|---|---|---|---|---|---|
| | *small* | *large* | *small* | *large* | *small* | *large* |
| $w = \infty$ | 45% | 40% | 50% | 35% | 38% | 30% |
| $w = 0$ | 25% | 15.5% | 17% | 20% | 24% | 20% |
| *w small* | 1% | 4% | 1% | 4% | 3% | 3% |
| $w = 1$ | 19% | 19% | 18% | 18% | 18% | 24% |
| *no rule* | 10% | 20.5% | 14% | 21% | 14% | 21% |

Table 6.17. Classification of the participants according to their forecast behaviour

**Synthesis and main results on forecasts**

***Result 1*: Participants in small groups coordinate on a common price forecasting strategy (their dispersion errors are smaller than the common errors), whereas in large groups participants experience coordination in mean (they are more dispersed around the mean).**

***Result 2*: Simple forecasting rules cannot explain price expectations (no easily exploitable pattern is common in the price structure).**

***Result 3*: About 50% of the subjects are perfect adjusters and perfect forecasters.**

***Result 4*: A tendency for overreaction is detected in price expectations.**

### 6.3.4. Production decisions

Production decisions are strictly related to the evolution of production earnings studied in a previous paragraph (the latest are implied by the firsts). Therefore, this section will not be focused on the study of production decisions *stricto sensus*; instead, production activity will serve as a benchmark for the analysis of some prerequisites of the eductive reasoning: we will first investigate about the coherence of participants behaviour through the study of the adequacy of one's production decisions with one's forecasts; if behavioural biases are highlighted, this analysis will be followed by the study of biases characteristics and their implications on the strategic behaviour.

At period $t$ a participant $i$ has to take two simultaneous decisions: a production decision, denoted $q_{it}$, and a price forecast, denoted $p_{it}^{e}$. Implications of rational choice suggest that $q_{it}$ and $p_{it}^{e}$ are related through the fact that both are consequences of the local profit maximization process: a player $i$ is thus coherent in decisions if $q_{it}$ and $p_{it}^{e}$ are mutually best-responses, i.e. when predicting price $p_{it}^{e}$, the player chooses an individual quantity $q_{ibest}$ best-responding to $p_{it}^{e}$. Analytically, given the underlying market equations depicted in chapter 5, $q_{ibest}$ can be calculated as $q_{ibest} = (p_{it}^{e} - d) \times c$, $c$ and $d$ are parameters defined earlier. If player $i$ is not coherent, the quantity $q_{it}$ he really chooses is biased, thus $q_{it} - q_{ibest} \neq 0$. Moreover, at quantity $q_{it}$ corresponds real realized price $p_t$; to quantity $q_{ibest}$ should correspond a best-response price, $p_{best}$, calculated as $p_{best} = \dfrac{A - \sum_{i=1}^{N} q_{ibest}}{B}$, with parameters $A$ and $B$ defined earlier. For a coherent participant, $p_t$ and $p_{best}$ should coincide. We will therefore compute for each participant and each group $q_{ibest}$ and $p_{best}$; we will then examine the differences $p_t - p_{best}$ and $q_{it} - q_{ibest}$; their extent and their signs will allow us to draw some lines on the behaviour of participants in this experiment.

Figures 6.7 and 6.8 display average market prices, forecast and best-response prices within small and large treatments. The series $p$ represents the average market (real) price into a treatment, calculated as the mean of all realized prices over all groups in an experimental setting (fast small, fast large, slow small etc…). The series *forecast* represents the average of individual forecasts over all participants in a treatment. The series $p_{best}$ represents the average over all groups within a treatment of all best-response prices calculated group by group as described earlier. On the graphs the REE price level is not represented but it sticks to the 60 - level line. Confirming our previous results, the market price and forecast series are very similar. Another general observation of these figures is that average market price and forecast are generally above or at the REE level, whereas best-response prices are at or below the REE level. The first graph depicts the evolution of these series in the *fast small* framework. Market prices and forecasts converge to the best-response price, almost confounded with the REE price, and remain slightly above; only on the last half of the experiment the hypothesis of equal market price and best-response price cannot be rejected at a 10 percent level. This implies that participants are not fully coherent in their decisions as long as they underproduce with respect to the quantity best-responding at their forecast. Indeed, as we calculate the difference $q_{it}$ - $q_{ibest}$, we find a negative sign for it in 71% of the decisions on average, but in this case the bias does not have an important impact because it is very small in absolute value (-5.57). In the slow small treatment, described in the second graph, market prices and forecasts durably remain above the best-response price; we thus can again identify here a coherence failure, as long there is a significant hiatus between production decisions that participants really take and production decisions that they should take in order to perfectly correlate them with their forecasts. 71% on average of the differences $q_{it}$ - $q_{ibest}$ are negative (this difference is about -14.14 on average), signifying that participants do not link their forecasts to their output decisions and they behave strategically. The picture for the small divergent treatment is more stylized: the gap between market price, forecasts and best-response price is significantly higher (-39.66) and no tendency to convergence is observed with time. Differences $q_{it}$ - $q_{ibest}$ are negative in 77% of choices. There is clear underproduction behaviour. Remember that in this particular treatment, if participants were to put into practice an eductive reasoning, prices and forecasts would experience chaotic divergent behaviour. When taking decisions, participants preserve them selves from the consequences of a divergent market and take decisions according to another type of computation. In conclusion, in small treatments, participants are not coherent with respect to best-response behaviour: they deliberately choose quantities to produce that are smaller than those which would best-responded to their forecasts. This behaviour could be the consequence of strategic thinking or of risk aversion and allows participants to face a relatively high price, consistent with the institution effect that we mentioned earlier in this chapter.

Figure 6.8 describes the evolution of market price, forecast and best-response price in large groups. The evolutions of these series are smoother than in small groups. Observations pointed our earlier still hold, but to a lesser extent. In particular, average values for $q_{it}$ - $q_{ibest}$ are -1.72 in fast treatment, -1.42 in slow treatment and -11.95 in divergent treatment and negative signs represent 58.12% in fast treatments, 59.12% in slow treatments and 74.24% in divergent treatments. In fact, absolute differences $q_{it}$ - $q_{ibest}$ have to be normalized according to the type of treatment: in small treatments, $q_{\mathrm{REE}} = 72$, and in large treatments, $q_{\mathrm{REE}} = 36$. Therefore table 6.18 reports for each treatment average percentages of underproduction ($q_{it} < q_{ibest}$) and normalized average biases $\dfrac{q_{it} - q_{ibest}}{q_{REE}}$. In absolute value, deviations in small groups are significantly higher than in large groups, and this inequality also holds for percentages of underproduction. However, if we compare these values with the Cournot and collusion equilibria values, we realize that the underproduction behaviour is close to this type of strategic behaviour only in the *divergent small* treatment.

| | *fast* | | *slow* | | *divergent* | |
|---|---|---|---|---|---|---|
| | *small* | *large* | *small* | *large* | *small* | *large* |
| $\frac{q_{it} - q_{ibest}}{q_{REE}}$ | -0.07 | -0.04 | -0.19 | -0.03 | -0.55 | -0.33 |
| % of $q_{it} < q_{ibest}$ | 71% | 58.12% | 71% | 59.12% | 77% | 74.24% |

Table 6.18. Underproduction figures

**Synthesis and main results on the quantity decision**

***Result 1*: Participants do not fully correlate their production decision and their forecast (they do not relate them by a best-response relation). This result is less evident in large groups.**

***Result 2*: Strong evidence of underproductive behaviour is found.**

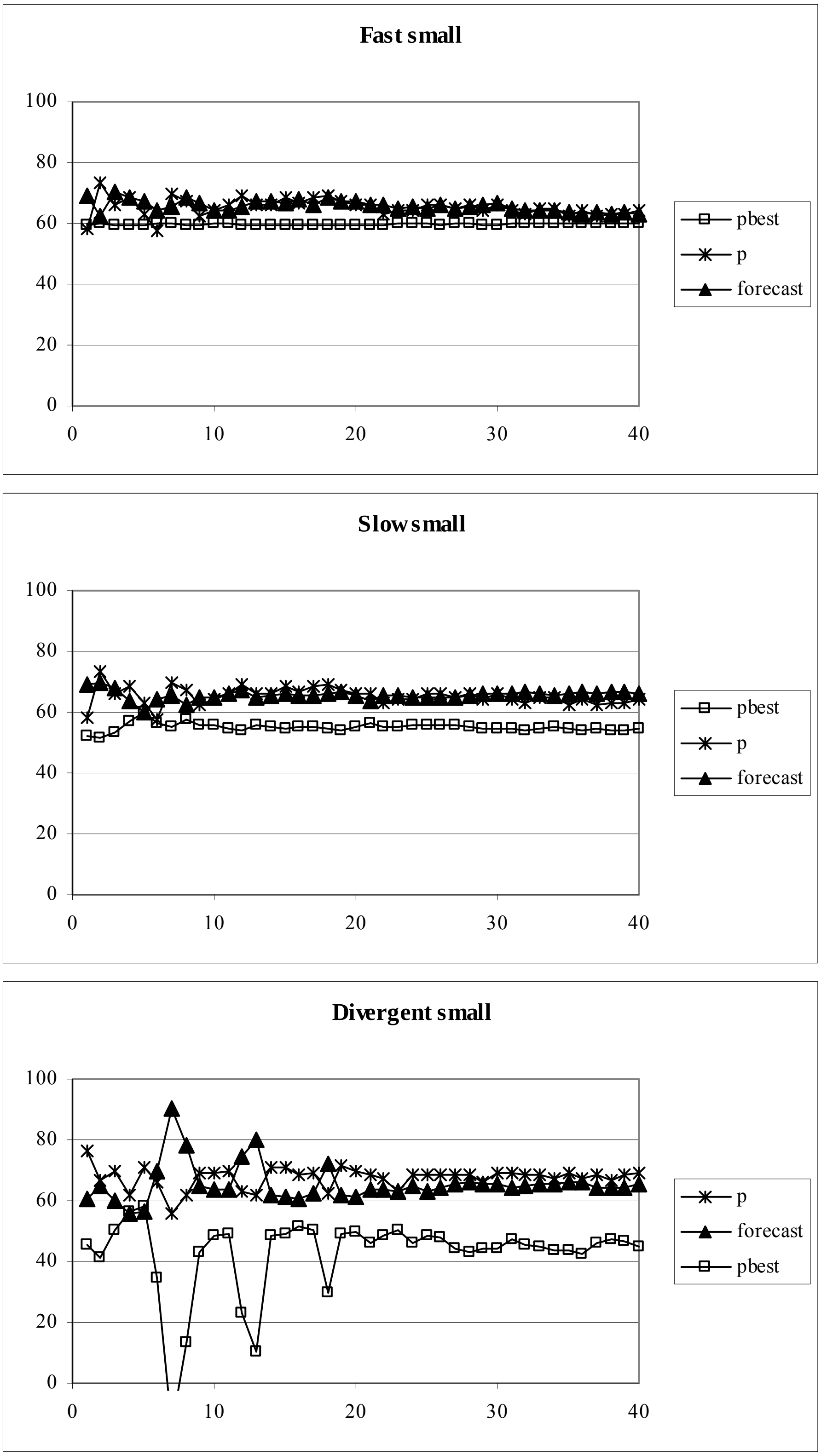



Figure 6.7. Average market price, forecast and best-response price in small treatments

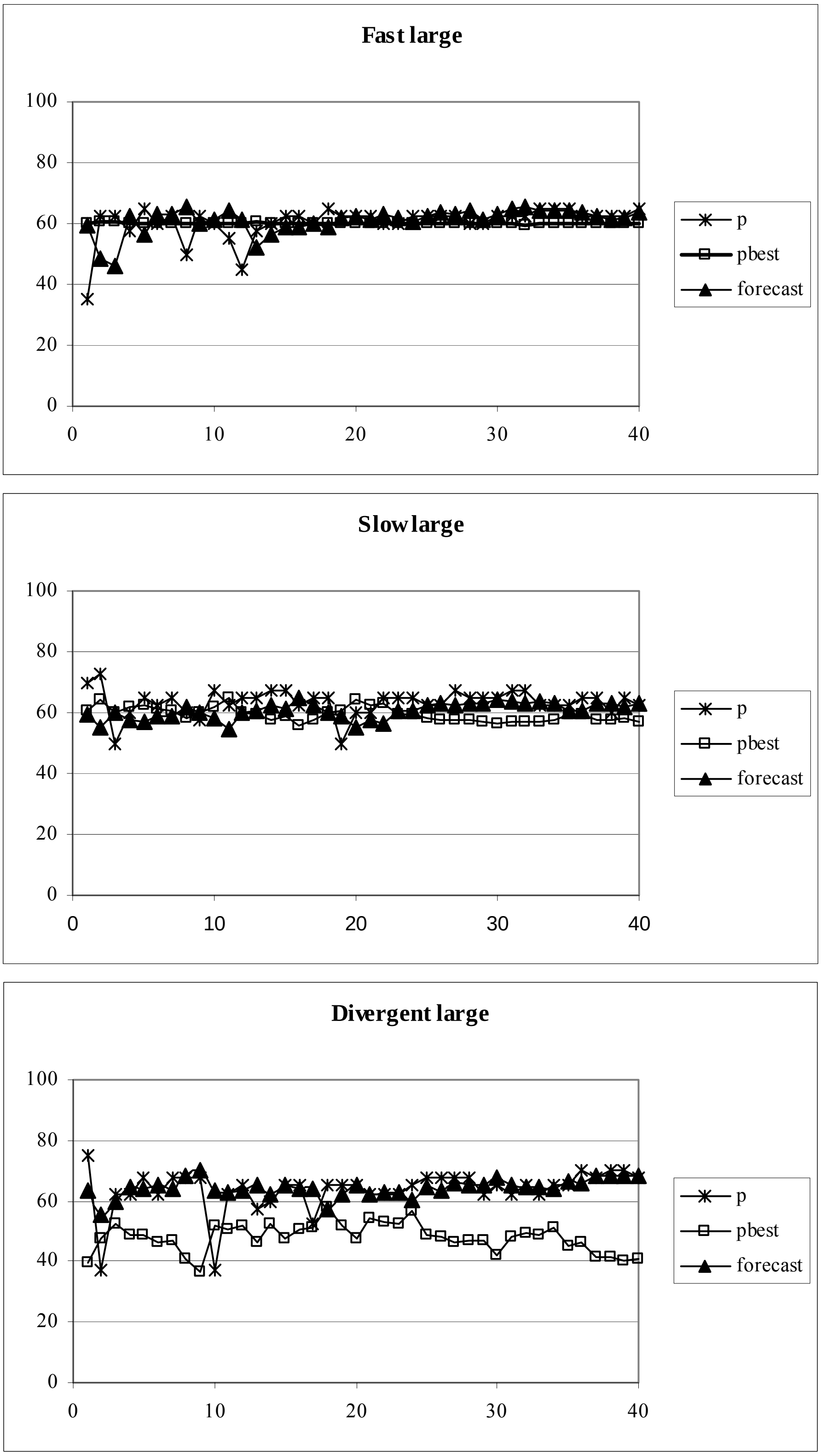
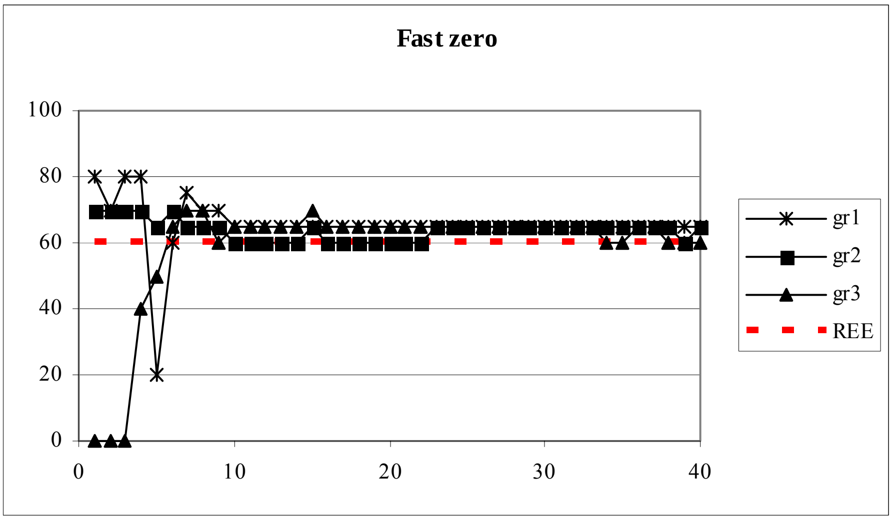
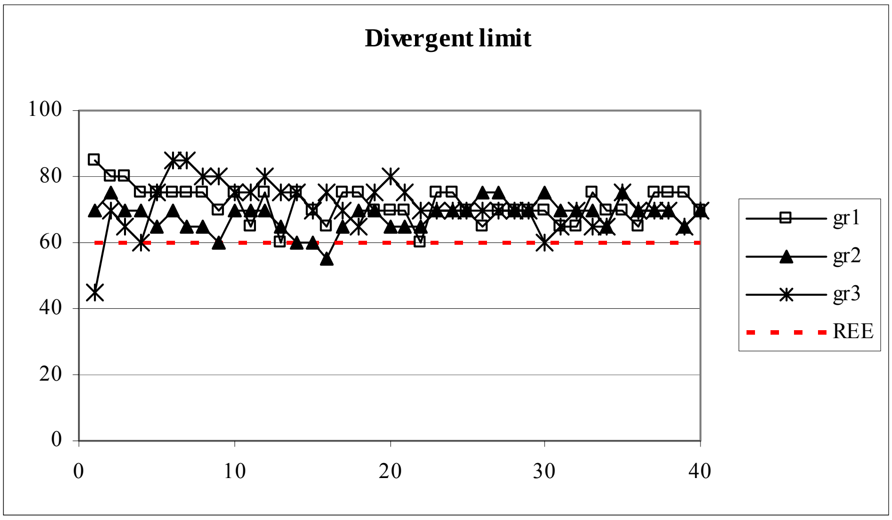



Figure 6.8. Average market price, forecast and best-response price in large treatments

### 6.3.5. Stress treatments

In this section we rapidly present main results on convergence and coordination that we obtained in the stress treatments. We remind that we tested a high endowment case, a zero-cost case and a constant marginal cost case. The idea behind the high endowment treatments was to test the power of the monetary incentives. Do participants in the high endowment treatment take more risky decisions? The idea behind the zero-cost treatment was to see whether participants still exhibit an underproduction profile. The constant marginal cost case corresponds to the limit case of divergence, where the supply curve as represented before is vertical; but this is a dual case, as the fixed marginal cost gives a strong indication of the REE market price. Figures 6.9 to 6.11 present the market price evolution for all groups in these treatments. Results in these treatments are not significantly different from results in "regular" treatments. However, in the *fast zero* treatment, the underproduction figure is reduced; in the *divergent limit* case the volatility is smaller; in the *slow high* treatment prices oscillate more.





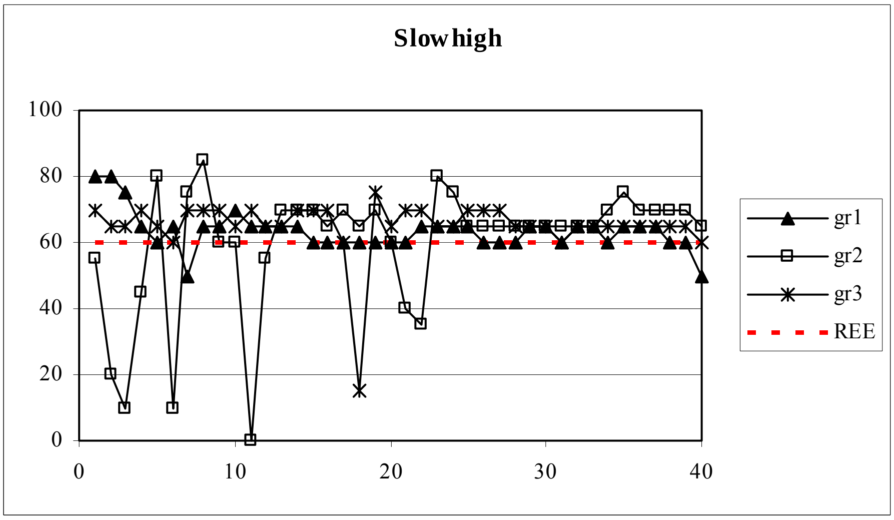




Figure 6.9. Price evolution in stress treatments

## 6.4. Discussion and conclusion

In this chapter we investigated the process of expectations formation in a linear cobweb market. In this type of market, edcutive and evolutive processes converge (if the conditions on the parameters are met) to an unique REE. While the underlying reasoning sustaining this type of equilibrium is well known, it remains an empirical issue to know whether agents are able to coordinate their beliefs and take actions that exactly confirm their beliefs. For example, does learning through repeated market interactions orient belief formation in the direction of a common expectation?

In this chapter we presented results of experiments whose objective was to investigate belief formation and learning in the cobweb model. Output decisions must be made one period before the production is sold on the market. Therefore, upon making their production plan, producers must anticipate the price their output will be sold for. Ex post, the selling price is determined according to the demand schedule and the aggregated output.

In order to address these questions, we investigated several other hypotheses: *do we observe coordination with time (emergence of similar profiles and learning)? Are participants, endowed with perfect knowledge about the market, able to perfect forecast it? Do they hold expectations coherent with their decisions? What happen in cobweb markets where theoretically chaos is expected? Do participants reach the REE? Do they put into practice some simple forecasting rules or do they sophisticate their reasoning when taking decisions?*

We considered two major distinctions in our treatments: one concerning the speed of the convergence process and the other the size of the market.

In order to investigate the speed of the convergence, we first transform the linear supply functions into step functions and after vary their slopes. For a large difference between the supply and the demand function slopes (in the favour of the demand function), the number of iterations until the REE is small (*fast* convergence), for small differences the number of iterations will be large (*slow* convergence). No theoretical convergence should occur when the slope of the demand function is smaller than the slope of the supply function (as defined in the chapter) (the *divergence* condition).

Subjects had two decisions to take: a production decision and a forecast decision. The decisions are simultaneous. Incentive schemes are put into practice for each type of decision: production decisions were rewarded according to a standard profit calculation (as a function of the quantity produced and the production cost) and forecast decisions were rewarded according to their quality: we implemented a quadratic scoring rule to guarantee truthful revelation of beliefs is incentive compatible.

We also compared small markets with large markets and some additional stress treatments.

We report here synthetic results that we justified in this chapter.

*i)* *For all treatments and each type of decision, in general, with time, subjects become more and more efficient, coordinated and exhibit similar behaviours (average earnings increase while standard deviations decrease). Meanwhile, forecast earnings evolution is smoother.*

*ii)* *In small groups, subjects are better forecasters, but they have significant higher learning potential in large groups, i.e. all types of agents are asymptotical good forecasters.*

*iii)* *Divergent groups exhibit some coordination (not expected) and learning, allowing us to conclude that the eductive hypothesis can be good description of behaviour only in convergent groups.*

*iv)* *Market prices series are stationary and asymptotically converge to common values lying in a close neighbourhood of the REE. No significant difference in the period of convergence exists between small and large groups.*

*v)* *No easily exploitable pattern for forecastability is found in the structure of the market prices (except for some slow groups).*

*vi)* *Participants in small groups coordinate on a common price forecasting strategy (their dispersion errors are smaller than the common errors), whereas in large groups participants experience coordination in mean (they are more dispersed around the mean).*

*vii)* *Simple forecasting rules cannot explain price expectations (no easily exploitable pattern is common in the price structure).*

*viii)* *About 50% of the subjects are perfect adjusters and perfect forecasters.*

*ix)* *A tendency for overreaction is detected in price expectations.*

*x)* *Participants do not fully correlate their production decision and their forecast (they do not relate them by a best-response relation). This result is less evident in large groups.*

*xi)* *Strong evidence of underproductive behaviour is found.*

## Contents

# Chapter 7

# Coordination in cobweb experiments with(out) elicited beliefs

## 7.1. Introduction

The experiments presented in Chapter 6 addressed empirically the rational expectations hypothesis implication of perfect coordination in beliefs in the simpliest market environment, the cobweb model. As our work aimed at dealing with the mental process undelying the convergence to an eductively-stable equilibrium, beliefs played a central role: reaching an eductively-stable equlibrium involves beliefs-based learning. In recent years a lot of theoretical and empirical efforts have been done on the question of how people form, hold and use beliefs in reasoning or learning processes when repeatedly acting in a simple environment or playing a simple game. While some authors[1] focus on the way that people learn by looking back at their experience and seeing what has been successful in the past (reinforcement learning), others[2] focus on looking to the past to update beliefs about opponent's future action (belief learning). Camerer and Ho(1999) select the best features of

[1] Roth and Erev (1998), Arthur (1991).
[2] Cheung and Friedman(1997), Boylan and El-Gamal(1993), Mookherjee and Sopher(1994, 1997), Rankin, Van Huyck and Battalio(1997), Fudenberg and Levine(1998).

both of these models (among other things) in their model of EWA learning. In all these approaches, however, authors form a conjecture on the fact that while past payoffs and actions are observable, beliefs are unobservable and thus they must be represented by proxies and inferred. For example, in the two most common belief learning models, the Cournot and fictitious play models, beliefs are either equivalent to the last period action of one's opponent, or an average of the previous actions of one's opponent. Rankin et al.(1997), Cheung and Friedman (1997) and Fudenberg and Levine's (1998) model of smooth fictitious play hypothesizes that beliefs can be represented as a weighted average of past actions (weighted empirical beliefs, with weights declining geometrically at some rate).

This chapter presents the results of a series of experiments where we directly elicited the beliefs of subjects using a *quadratic scoring rule*, which provided subjects with an incentive to report their beliefs truthfully *and* compares results with an completely symmetric environment where beliefs are not elicited. In the literature these elicited beliefs are called the subjects' "stated" beliefs. As a result, this chapter presents an investigation of beliefs coordination where all relevant variables are observable, i.e., we study belief learning using elicited beliefs versus the opposite case of non-observed beliefs.

Our experimental design relies on a linear cobweb model where the equilibrium can be obtained through eductive reasoning, i.e. iterated elimination of dominated strategies (Guesnerie (1992)). We manipulate two treatment variables: the "speed" of convergence (as in the previous chapter) and *belief elicitation*. We compare sessions with and without belief elicitation to test whether explicit belief elicitation favours the type of (eductive) reasoning underlying the convergence process towards equilibrium. Early experiments on the "guessing game" (Nagel, 1995) suggested that subjects' beliefs are poorly coordinated. In contrast, in a market environment where subjects choose output levels, our previous results show that decisions are strongly correlated, although not necessarily on the equilibrium price level. Meanwhile, coordination in beliefs does not imply coherence with the related decisions (production activity). This constitutes the first question that we want to adress within this chapter: what is the use that subjects make of the elicited beliefs? The results presented in the previous chapter indicate that subjects do not best-respond to their stated beliefs: what do they best-respond to?

Comparing sessions with/without beliefs elicitation allows us to answer one possible criticism of the use of stated beliefs, i.e. the forecasting activity intensifies the difficulty of the task that the subjects have to accomplish at each period. A related question that we can explore within this comparison is if the elicitation setting induce a focusing on the task and allows subjects to better perform in that particular activity. Another criticism of the use of the elicitation technique is that stated beliefs usually are not available outside of the laboratory, and hence out of sample predictions would be difficult to make. It is important to note, however, that there exist a wide variety of survey data elicitating beliefs about various economic variables (that could be used in a belief learning model).

We therefore consider that for our research question on the eductive reasoning, it is important to have precise information about beliefs of economic agents; as in real markets this opportunity is not evident, it is equally important to collect data on the same activity without eliciting beliefs and to compare the results. Thus asking agents to report their beliefs is an interesting possibility. In the literature, there has been a large debate on the reward that the experimenter should give to the subject whose beliefs are elicited. As pointed out by Sonnemans (2001), when doing so, a researcher has to make a decision whether to reward agents for stating their beliefs or not. Without salient incentives, there is a danger that agents do not take their task seriously and that their reports are noisy. An experimenter may therefore opt to use one of the incentive mechanisms discussed in the literature (Murphy and Winkler, 1970; Savage, 1971; Holt, 1986). Agents who are rewarded with a payoff generated by a strictly proper scoring rule will truthfully reveal their beliefs when they maximize expected value (or expected utility with a linear utility function). Murphy and Winkler (1970) discuss three strictly proper scoring rules: the logarithmic, the spherical and the quadratic scoring rule. Of these, the Quadratic Scoring Rule (QSR) has been used most frequently[3].

We adopt in this chapter the QSR to reward stated beliefs. Does the QSR motivate subjects to exert more effort on the task, and to formulate better beliefs? Some early psychological studies (Beach and Philips 1967, Jensen and Peterson 1973) suggest that there is no

[3] Sonnemans (2001) cites McKelvey and Page (1990), who use it in an experiment on information aggregation, Friedman and Massaro (1998), in an individual learning experiment; Nyarko and Schotter (2000) in a study on belief learning in a strategic game with a unique mixed strategies equilibrium. Kraemer and Weber (2001) use the QSR in an experiment in which subjects sequentially process information about their predecessor’s beliefs and, if they are willing to pay, some private information. McDaniel and Ruthström (2001) make use of the QSR in an individual problem solving experiment. Huck and Weizsäcker (2002) elicit beliefs of one group of subjects for another group of subjects’ choices between lotteries. They compare beliefs elicited via a QSR procedure with beliefs elicited via a Becker-DeGroot- Marshak pricing rule, and conclude that the QSR procedure yields more accurate beliefs. Offerman, Sonnemans and Schram, 1996, 2001, Sonnemans, Schram and Offerman, 1998, 1999 and Offerman and Sonnemans 1998, use it to elicit subjects' beliefs in public good games, individual decision tasks and the hot response game.

difference in performance between subjects motivated by a proper scoring rule and subjects not motivated by monetary incentives. Another study by Friedman and Massaro (1998) on beliefs in a probability matching task does not find significant differences between paid and unpaid subjects. However, the latter paper suggests that relatively more of the unpaid subjects were unmotivated (in the sense that they repeatedly reported the default probability value 0). The Quadratic Scoring Rule is theoretically a good instrument to elicit beliefs provided that respondents are risk neutral and do not distort probabilities. It has been criticized for these assumptions. In an experiment, Sonnemans (2001) presented a way to correct reported beliefs for the possible biasing effects of risk attitudes and probability weighting. He found that in practice these factors do not affect subjects' reported beliefs in an undesired way. This is reassuring news for previous studies that made use of QSR procedures without a correction device. As usually experimental economists are very sceptical about the value of data that are generated without salient incentives, we still believe that rewarding subjects for reporting their beliefs is the preferred procedure.

Our data does not support the hypothesis that belief elicitation favours the coordination of subjects' decisions. However, in all sessions, even for those where divergence was predicted, we observe strong coordination on a price level that is slightly above the rational expectation equilibrium price.

Section 7.2 briefly presents the backgroud of the model; experimental procedures are presneted in section 7.3 and results in section 7.4; section 7.5 concludes.

## 7.2. Model background

To be more precise, let us remind the price adjustment process in the linear cobweb model. As the marginal cost of each producer is given by $MC(q) = q/c+d$, the total cost function is given by the quadratic form $C(q) = q^2/2c+dq$. With $N$ identical "small" producers on the market, aggregate supply is given by $S(p) = C(p-d)$, with $C = Nc$. Assume that aggregate demand is a linear function $D(p) = A - Bp$ if $A- Bp > 0$, and 0 if not, with $A, B > 0$. The Rational Expectation Equilibrium (REE) is reached when the price $p$ is equal to the marginal cost. At the beginning of each period producers choose their output level and at the end of the period all units produced must be sold at the prevailing market price. The equilibrium price can be reached through eductive reasoning if the condition $B > C$ is met, i.e. the slope of the demand function is higher (in absolute value) than the slope of the supply function.

The process of iterative elimination of aggregate output levels narrows down the set of possible output levels until the equilibrium price is reached[4]. At that price only one output level is possible, and since all producers are identical, they all produce the same fraction of total output.

**Beliefs elicitation**

In the "guessing game", a subject's task is to guess a number implying that his expectation coincides with his decision. Expectations are therefore observable in guessing games. In contrast, in cobweb market experiments subjects have to make output decisions, based on their beliefs about the market price. In the standard experiment, the subject's price expectations are therefore not observable. To make an inference about the unobserved expectation requires an assumption relating beliefs to output decisions. Furthermore, it is not obvious whether the subject's mental process leading to their output decision is based on a price expectation.

In order to understand how they take into account their beliefs and how these beliefs evolve with experience, we elicited subject's beliefs in several sessions of the experiment. Belief elicitation has several advantages: it allows us to test whether output decisions are correlated with beliefs, we can study how beliefs are updated with previous market experience, and finally we can investigate our main question whether subjects are able to coordinate on a common price expectation. On the other hand, elicitation focuses the subject's attention on a particular process of reasoning for taking their output decision. Thus may favour the coordination of beliefs. Our hypothesis is therefore that belief elicitation facilitates coordination on a common expectation. In order to test this assumption, we compare sessions with belief elicitation to sessions without.

**Hypotheses**

Following our previous discussion we summarize the hypotheses to be tested as five short statements:

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[4] $p_n = \frac{A+Cd}{B} \times \frac{1-(-1)^n\left(\frac{C}{B}\right)^n}{1+\frac{C}{B}} + \frac{A+Cd}{B} \times (-1)^n \left(\frac{C}{B}\right)^n p_o$, $\lim_{n\to\infty} p_n = \frac{A+Cd}{B+C} = p^*$( when $B>C$)

$H_1$) (**learning**) subjects learn in both types of treatments (with and without belief-elicitation);

$H_2$) (**coordination**) subjects are able to coordinate their beliefs for both types of treatments depending on the speed of convergence;

$H_3$) (**coherence**) in sessions with belief elicitation, subjects use their beliefs to better choose their individual output level;

$H_4$) (**eduction**) subjects' decisions are based on an *eductive*-type of reasoning independently of belief elicitation;

$H_5$) (**elicitation**) *belief elicitation improves coordination, and favours eductive learning, leading to higher output earnings*;

In the result sections we shall focus on $H_5$, our main hypothesis. However, we cannot investigate $H_5$ independently, and therefore we address also hypotheses $H_{1\text{-}4}$.

## 7.3. Experimental procedures

This experiment is based on the same protocol as the one in the previous chapter. Each subject plays the role of a producer of a perishable good, sold on the market and produced one period before. However, about half of them only have to take production decisions, and the remaining subjects have to simultaneously provide a price forecast. The goal of the experiment is to observe the differences in convergence to a price between these two types of treatments. The parameters of this experiment are the same as in the previous chapter; we summarize them here after insisting on the description of the parameters that are specific to the present experiment, i.e. belief elicitation.

Our interest treatment variable is belief elicitation. In order to prompt the type of reasoning underlying iterated dominance solvability, we asked subjects in some sessions to state their beliefs about the prevailing market price explicitly. This was implemented by using a payment scheme which rewarded the accuracy of the prediction with respect to the realized market price. Our hypothesis is that in sessions with belief elicitation, learning would be faster and more oriented towards the equilibrium price. Furthermore, in sessions with belief elicitation we are able to investigate the consistency of subject's output decision with respect to their price expectation.

Table 7.1 summarizes our experimental design based on a 2×3 factorial design. The cells indicate the number of independent observations collected in each condition. One observation corresponds to a group of 5 subjects interacting over 40 periods. Each treatment has a name composed of two characteristics: one for the speed of convergence (fast, slow, divergent), and one for the belief elicitation (with=yes, without=no).

| | | Convergence condition | | |
|---|---|---|---|---|
| | | *Fast Convergence* | *Slow Convergence* | *Divergence* |
| Belief Elicitation | *Yes* | 6 | 6 | 6 |
| | *No* | 3 | 3 | 3 |

Table 7.1. Summary of the experimental design (number of independent markets)

- Each session involved 5 subjects interacting during 40 periods in a cobweb market as described previously. Communication between subjects was not allowed. At the beginning of the experiment subjects received a fixed endowment of currency units, called *capital*. After each period earnings were added to the initial capital and losses were subtracted. The initial capital was constant across treatments. At the end of each period, subjects were informed about the prevailing selling price, their production cost, their profit or loss and the remaining capital. In treatments with belief elicitation they were also informed about their forecast earnings. Furthermore, subjects could see at any time their past data by clicking a *history* button. Each session begun with two trial periods in order to familiarize subjects with the graphic interface. The subjects' understanding of the instructions and procedures was checked by a short computerized questionnaire submitted before the beginning of the experiment. During the experiment, the subjects could make written comments on a sheet. Subjects involved in this experiment had never participated before in a similar experiment. A total of 135 subjects participated. They earned between 6 and 30 euros for an average time of 90 minutes per session[5]. The experiments were conducted at the LEES laboratory between July 2002 and July 2003, on the basis of a computer network.

[5] The participants in the sessions were students, randomly selected from a large subject pool of 1500 volunteers. The pool includes students from all disciplines from the universities of Strasbourg and is refreshed every year; the experimental history of each subject his recorded, together with individual data.

- Each producer had to choose an integer valued output level at each period (supply and demand functions were thus defined as step functions, in discrete (integer) units). This implies the convergence towards the REE in a finite number of eductive iterations. By changing the shape of the supply or the demand curve, we compare treatments with a small number of steps ("fast convergence") to treatments with a large number of steps ("slow convergence") and also consider the case of divergence, i.e. treatments where convergence is impossible according to the eductive reasoning, because the slope of the supply curve is larger than the slope of the demand curve. *B*, the slope of the demand function is held fixed, and we vary the slope of the supply curve, *C* (we consider a small value and a large value for *C*). For a small relative value of *C* the number of iterated dominance reasoning steps is also small, therefore we hypothesize that subjects will have less difficulty to coordinate on the equilibrium belief (the process will be faster for low *C* than for large *C*). The names bit based on the speed of convergence is therefore, as in our previous chapter, *fast* for the treatment with large difference $B - C$, *slow convergence* for the treatment with small difference $B - C$, and *divergent* for an additional treatment for which $B - C < 0$.

- Subjects received written instructions containing detailed information about the aggregate demand function and their individual marginal cost function. The demand function is decreasing with price and the marginal cost function increasing with price. The demand and cost functions are presented to subjects as tables. The levels of individual output are grouped into intervals of homogeneous size in each treatment. To each interval corresponded a different level of marginal cost, in multiples of 5. Table 7.2 summarizes the parameter values that were chosen for the different treatments.

| | *fast* | *slow* | *divergent* |
|---|---|---|---|
| *A* | 900 | 900 | 900 |
| *B* | 9 | 9 | 9 |
| *c* | 1/10 | 8/5 | 21/5 |
| *C* | 5/10 | 8 | 21 |
| *d* | -660 | 15 | 300/7 |

Table 7.2.Parameters of the experimental treatments

- Subjects knew that all subjects in a market had the same information, the same characteristics and were required to make the same type of decisions simultaneously: it was common knowledge to the subjects in each session that the individual marginal cost functions were identical and that all subjects received the same instructions; subjects also knew that the sum of the individual productions determined total output, and that the output had to be sold within the period, so that the selling price was determined according to the demand schedule.

- The aggregate demand function is defined on { 0,1,…900 }. This function is identical for all the treatments, as indicated in table 7.2. The upper limit of this interval determines the capacity of the market or the total output (for a higher quantity the selling price is zero). All possible choices for the total output are divided into 21 homogeneous intervals of amplitude 45 units. Each interval of total output determines a selling price. The maximum price is obtained for a zero demand and it is equal to 100.

- The reward for correct forecasts was a flat rate of 1000 experimental currency units. This amount was reduced in proportion of the forecasting error according to a quadratic error term: $\Pi_{f\,t} = 1000 - 0,8 \times (p^e_t - p_t)^2$. $\Pi_{f\,t}$ represents the profit or loss of the forecast, $p^e_t$ is the price forecast for period t and $p_t$ the prevailing selling price in period $t$.

- The profit obtained from forecasting was added to the profit resulting from the output decision defined in the standard fashion: $\Pi_{q\,t} = q_t \times p_t - TC\ (q_t)$, where $\Pi_{qt}$ is profit for the current period, $q_t$ the subject's output choice and $TC$ the total production cost. $\Pi_{qt}$ can be positive or negative, according to values taken by the prices, rising from the aggregation of the individual decisions.

The elicitation of price forecasts should favour the coordination and the convergence in the cobweb model, especially because price forecast are rewarded according to the quadratic scoring rule. This should lead subjects to coordinate their beliefs and move therefore faster to the equilibrium price.

## 7.4. Results

In this section, we present five results with several analyses in order to address the five hypotheses that we stated earlier. Thus, our first result makes clearer the learning hypothesis, while the second address the coordination-related hypothesis. With analysis provided for result 3, we inquire about the coherence of subjects decisions. The 4th result tries to validate our hypothesis about the existence of an eductive-type of reasoning. Last result reports on the use that subjects make of the forecast task.

***Result 1*: Learning is detected in both types of treatments.**

We make the assumption that learning helps improving output earnings. However, this is possible only in convergent groups (in divergent groups, making use of the same type of learning should decrease earnings). Therefore, we present rough indicators on learning only in convergent groups. Divergent groups are investigated in subsequent analysis.
In order to illustrate this result, we look for differences in output earnings induced by belief elicitation. Table 7.3 summarizes our observations in terms of average output profit ($\overline{\pi}_q$) and standard deviations ($\sigma$) for the first 20 periods (*1-20*) and for the last 20 periods (*21-40*). Averaging over the two sub-periods allows us to detect a rough effect of learning and to verify $H_1$. As we see from table 7.3. our rough indicators already show the effect of learning with repetition. The average profit from the production activity increases with repetition, both for the *fast* and *slow* treatments *with belief elicitation*[6]. In order to test this conclusion for *without data*, as we only have 3 independent measures in each type of treatment, we provide further analysis in the next paragraph.
In order to test $H_1$ for *without* data, and to strengthen our previous non-parametric results for $H_1$ for *with* groups, we set up a more refined analysis of learning by taking into account the 40 periods. In order to do so, for all groups, all treatments and all periods, we introduce the *time* variable in a regression on past realized prices, to predict the average output profit of a group, as follows:

$$\Pi_{q\,t} = \beta_1 p_{t-1} + \beta_2 t + \varepsilon_t, \quad t=\{1,\ldots 40\}$$

[6] this is supported by a Wilcoxon rank sum test ( $p<0,03$)

| $\overline{\pi}_q$ (σ) | | fast | | slow | | divergent | |
|---|---|---|---|---|---|---|---|
| | | *with* | *without* | *with* | *without* | *with* | *without* |
| Periods 1 to 20 | *gr1* | 843 | 2881 | 1317 | 1862 | 1033 | 909 |
| | | *(12670)* | *(801)* | *(290)* | *(535)* | *(315)* | *(399)* |
| | *gr2* | 3136 | 3207 | 1830 | 1359 | 927 | 1000 |
| | | *(1409)* | *(693)* | *(516)* | *(2115)* | *(382)* | *(369)* |
| | *gr3* | 2902 | 3363 | 479 | 1546 | -568 | 942 |
| | | *(1668)* | *(781)* | *(4850)* | *(304)* | *(9543)* | *(385)* |
| | *gr4* | 2841 | | 1535 | | -1629 | |
| | | *(1448)* | | *(1067)* | | *(11252)* | |
| | *gr5* | 3094 | | 1812 | | 823 | |
| | | *(1001)* | | *(549)* | | *(348)* | |
| | *gr6* | 3293 | | 1625 | | 762 | |
| | | *(835)* | | *(739)* | | *(227)* | |
| Periods 21 to 40 | *gr1* | 3427 | 3511 | 1527 | 1853 | 917 | 611 |
| | | *(971)* | *(516)* | *(195)* | *(249)* | *(256)* | *(350)* |
| | *gr2* | 3433 | 3654 | 1883 | 1893 | 719 | 900 |
| | | *(800)* | *(200)* | *(256)* | *(275)* | *(1552)* | *(217)* |
| | *gr3* | 3638 | 3738 | 1370 | 1544 | 709 | 783 |
| | | *(256)* | *(166)* | *(504)* | *(330)* | *(274)* | *(250)* |
| | *gr4* | 3544 | | 1657 | | 1138 | |
| | | *(455)* | | *(280)* | | *(447)* | |
| | *gr5* | 3134 | | 1871 | | 844 | |
| | | *(593)* | | *(216)* | | *(228)* | |
| | *gr6* | 3460 | | 1665 | | 552 | |
| | | *(260)* | | *(466)* | | *(359)* | |

Table 7.3. Average earnings and standard deviation according to treatments and periods

In order to accept $H_1$ the coefficient of the time variable ($\beta_2$) should be significant and positive for convergent groups, i.e. the average output profit increases with repetition due to learning. Table 7.4 summarizes for our 27 groups, and all treatments, the significance level for the *t*-test. When a negative sign is found for the *t*-test, the coefficient $\beta_2$ of the time variable is also negative. For almost all the *fast* and *slow* groups, the time variable is significant and exhibits positive coefficients. This is true for only one *divergent* group.

| | | fast | | slow | | divergent | |
|---|---|---|---|---|---|---|---|
| | | *with* | *without* | *with* | *without* | *with* | *without* |
| *group* | *gr1* | 2,86 | 7,55 | 3,59 | 2,64 | *-1,21* | *-1,47* |
| | *gr2* | 5,35 | 3,83 | 3,96 | 2,26 | *0,27* | *0,15* |
| | *gr3* | 4,42 | 6,31 | 2,08 | *1,66* | 2,16 | *-1,18* |
| | *gr4* | 4,74 | | *1,44* | | *0,64* | |
| | *gr5* | *0,76* | | 2,10 | | *1,12* | |
| | *gr6* | 3,12 | | *1,80* | | *-1,38* | |

Table 7.4. Significance levels (*t-test*) and sign (+/-) for time variable

Table 7.3 exhibited several interesting features, almost common to all treatments. First, the average output profit increases between sub-periods in all treatments except for the treatments *divergent,* where most of the coefficients are negative or not significant. Since the average profit increases, subjects become more and more “efficient”, a fact that is compatible with our learning hypothesis ($H_1$), if we consider that the learning increases efficiency. Second, we observe that the variability of profits decreases sharply from the first sub-period to the second. In other words, individual differences decrease with repetition which suggests that subjects’ choices become closer to each other in the second half of the experiment than in the first half. This observation supports our coordination hypothesis $H_2$, which will be addressed later. The $\beta_2$ values in table 7.4 for the *divergent* cases support our hypothesis $H_4$ as stated in the second part of the result 1 paragraph, because the application of *eductive* reasoning to the divergent treatment implies that subjects become less and less efficient. As $\beta_2$ values for the divergent case are negative, this implies that, with time, subjects in those treatments do not improve their profits, which could be consistent with an evolution through an eductive type of reasoning. Our observations are compatible with the earlier results of Hommes and al. (2002).

***Result 2:*** **Subjects coordinate in all types of treatments.**

The fact that total output is sold at the market demand price, the REE, implies that, with our assumptions and choice of parameters, the price is the same in all treatments: 60 currency units per unit of output. We address the coordination hypothesis by analysing the price behaviour in each treatment. If participants in a market are coordinated, market price should exhibit almost stationary behaviour, without excess volatility.

Table 7.5 presents the average market price and the standard deviations calculated for each group, and each treatment. According to table 7.5, there are few differences in average realized prices between groups and across treatments. Average prices do not differ much between groups with elicitation and groups without elicitation. However, since market prices could only take values in multiples of 5, in most cases the average market price is only 1 or 2 steps away from the REE equilibrium. Notice however that all average prices are above the REE price which is equal to 60. Therefore there is a tendency for subjects to choose output levels below the equilibrium level. This implies that prices will converge to the REE state from above, which confirms an institution effect - our design is close to PO markets, where average price are at or above the Nash range (Holt, 1993), but not surplus analyses (Smith, 1962): in DA markets, if producers surplus exceeds consumers surplus (the case in our *convergent* theoretical design), price tends to converge to the competitive level from below and from above if the reverse situation). But as Holt pointed out, institution effect is always more important than surplus effect.

| Group | | | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|---|
| *With Belief Elicitation* | fast | Mean | 68,8 | 70,3 | 65,3 | 63,8 | 61,3 | 61,8 |
| | | *SD* | *15,8* | *4,4* | *5,8* | *3,7* | *3,8* | *2,9* |
| | slow | average | 60,6 | 69,6 | 59,6 | 66,8 | 68,3 | 69,8 |
| | | *SD* | *2,5* | *3,3* | *9,2* | *6,8* | *4,4* | *2,5* |
| | divergent | average | 70,5 | 68,6 | 63,6 | 71,2 | 67,8 | 64,1 |
| | | *SD* | *3,8* | *6,6* | *12,2* | *19,7* | *4,1* | *4,1* |
| *Without Belief Elicitation* | fast | average | 63 | 62,75 | 64,5 | | | |
| | | *SD* | *3,3* | *3,2* | *2,5* | | | |
| | slow | average | 70,1 | 68,8 | 62,8 | | | |
| | | *SD* | *4,4* | *7,1* | *3,6* | | | |
| | divergent | average | 67,5 | 71,4 | 68,8 | | | |
| | | *SD* | *7,5* | *6,4* | *5,8* | | | |

Table 7.5. Average market price (and standard deviation) per treatment per group

The market price converges to a common value in all independent groups. This result is supported by unit root tests (see Appendix). All market price series are level stationary (*I(0)*)[7]. This result clearly shows that price not only converge, but also remain at the convergence level in all markets, supporting our coordination hypothesis $H_2$ and empirically confirming the stability of the equilibrium (when producers have reach the equilibrium level, they remain at the global production level which provided this equilibrium point).

Figure 7.1 plots the price dynamics per group for each treatment. In all cases there is a clear convergence towards a common price that is slightly above the REE price. Furthermore, deviations occur more frequently in early periods than in late periods.

In order to estimate the asymptotic convergence point of the price level, we apply the method suggested by Noussair and al. (1995), allowing answering the question about the

[7] A series is defined as weakly stationary if it has a finite mean, finite variance and finite covariances, all of which are independent of time. With standard notations ($p$ stands for the market price), this means that: $\forall t$, $E(p_t) = \mu$ (constant), $Var(p_t) = \sigma^2$ (constant), $cov(p_t, p_{t+h}) = \gamma(h)$

direction of convergence. In order to do so, for every group price series we run the following regression:

$$p_t = p^{\infty}\frac{(t-1)}{t} + \frac{p^0}{t} + \varepsilon_t\,,$$

where $\varepsilon_t$ is a white noise; $t$ stands for the time variable; $p^{\infty}$ is the asymptote of the dependent variable and $p^0$ is the origin of a possible convergence process. Table 7.6 presents the results for all 27 groups. All variables are significant (*t-test)* and $R^2$ values vary from 0.3 to 0.8 according to the group. We find two results:

*i)* there is a convergence point in each treatment (supporting the coordination hypothesis). On average, the convergence point is at the REE or slightly above (one step away).

*ii)* at a 5% significance level we cannot reject the hypothesis of equals asymptotes ($p^{\infty}$) for all groups and all treatments, although if in the *divergent* groups there is a tendency of higher convergence points. This means that the ultimate point of convergence is the same between groups.

| | | fast | | | | slow | | | | divergent | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | *with* | | *without* | | *with* | | *without* | | *with* | | *without* | |
| | | $p^0$ | $\boldsymbol{p^{\infty}}$ | $p^0$ | $\boldsymbol{p^{\infty}}$ | $p^0$ | $\boldsymbol{p^{\infty}}$ | $p^0$ | $\boldsymbol{p^{\infty}}$ | $p^0$ | $\boldsymbol{p^{\infty}}$ | $p^0$ | $\boldsymbol{p^{\infty}}$ |
| *group* | *gr1* | 30,7 | **73,4** | 70,9 | **62** | 58,7 | **60,8** | 85 | **68,3** | 79 | **69,4** | 93,2 | **64,4** |
| | *gr2* | 65,7 | **70,9** | 69,5 | **62** | 81,1 | **68,2** | 83,4 | **66,9** | 74,3 | **67,6** | 97,4 | **68,2** |
| | *gr3* | 80,1 | **63,6** | 70,7 | **63,8** | 64,5 | **59** | 74,1 | **61,3** | 50,9 | **65** | 89,3 | **66,2** |
| | *gr4* | 69,6 | **63** | | | 90,7 | **63,8** | | | 81,8 | **69,9** | | |
| | *gr5* | 67 | **60,7** | | | 79 | **67** | | | 77,2 | **66,7** | | |
| | *gr6* | 67,4 | **61,2** | | | 78,4 | **68,7** | | | 71,6 | **63,2** | | |
| | *mean* | 63,4 | *65,4* | 70,3 | *62,6* | 75,4 | *64,5* | 80,8 | *65,5* | 72,4 | *66,9* | 93,3 | *66,2* |

Table 7.6. Asymptote ( $p^{\infty}$)and origin ($p^0$) of the convergent process for prices[8]

[8] for $t = 1$, $p_t = p^0$ and $\lim_{t\to\infty} p_t = p^{\infty}$

The next graphs consolidate our previous results. As shown in Table 7.5. (the standard deviation values), the evolution of market prices in the "without" treatments (right side) is smoother than in analogous "with" treatments (left side).

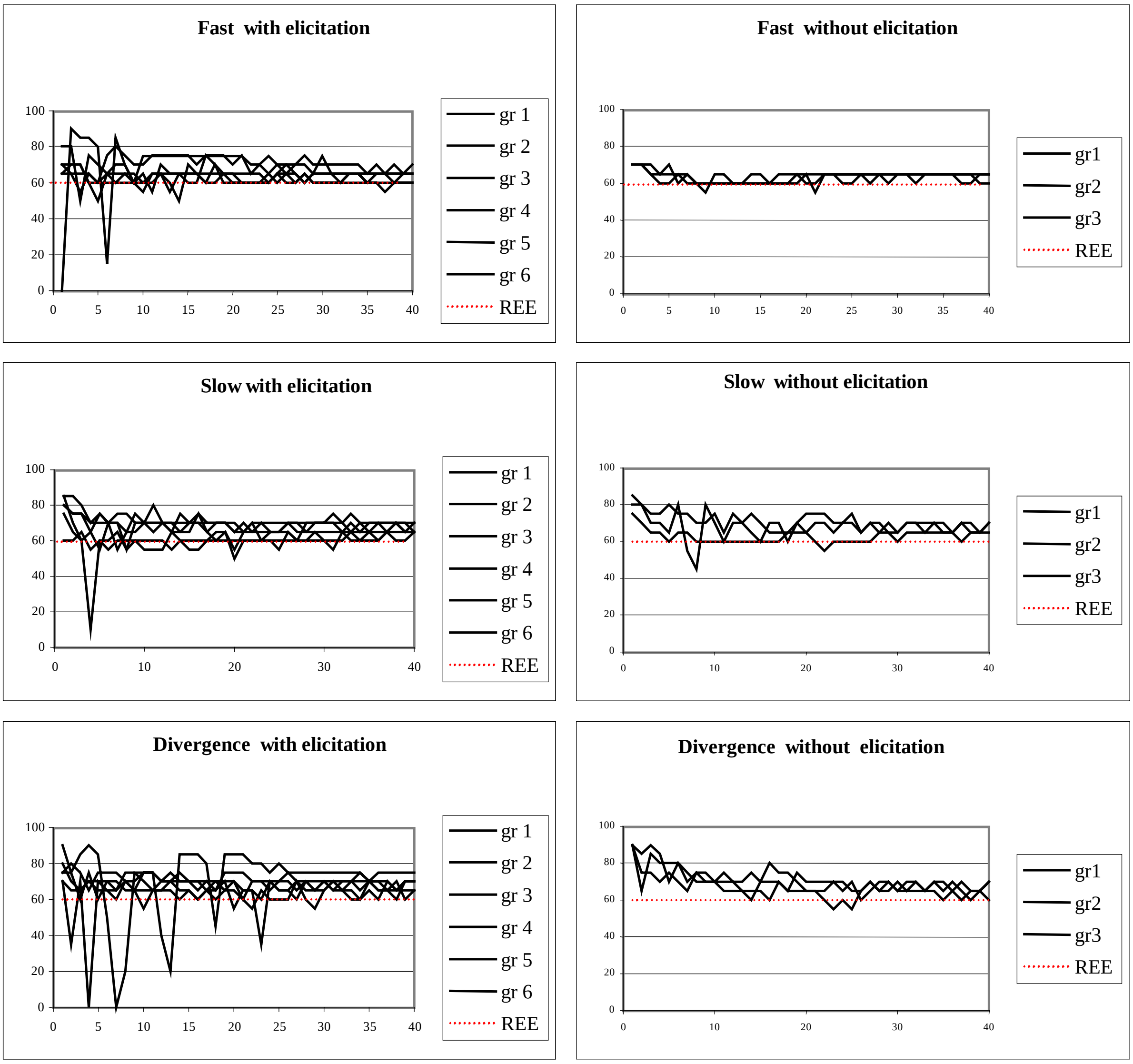


Figure 7.1. Market price evolution per treatment

While prices convergence to a common value, convergence might happen more or less early according to groups or treatments. We therefore analyse the period of convergence group by group. We define the convergence period (noted *h*) as the time period at which the market price enters into a "restricted price interval" and remains in it until the last period. We call this interval the *interval of convergence* and the corresponding period the *convergence* *period*. Convergence is thus characterized by two attributes: its type (strong, moderate or weak) and its speed (fast or slow). According to the amplitude of the convergence interval, we shall speak about strong convergence (in a narrow interval) and weak convergence (in a broad interval).[9]Since all the groups, even within the same treatment, do not converge at the same period, we compare the relative periods of convergence and try to see whether we can observe outstanding differences in speed of convergence. Table 7.7. presents the speed of convergence for all treatments and all groups. Treatments with belief elicitation do not seem to converge faster than their counterpart without belief elicitation. Furthermore, treatments for which convergence is fast do not converge faster than treatments with slow convergence.[10] Although further investigation is required, these findings seem to contradict the predictions of the eductive reasoning hypothesis $H_4$ for the *divergent* groups.

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| ***with*** | *fast* | 2 | 5 | 7 | 9 | 17 | 18 |
| | *slow* | 1 | 2 | 5 | 11 | 20 | 23 |
| | *divergence* | 2 | 9 | 10 | 21 | 23 | 30 |
| ***without*** | *fast* | 4 | 5 | 9 | | | |
| | *slow* | 5 | 18 | 32 | | | |
| | *divergence* | 6 | 18 | 25 | | | |

Table 7.7. Convergence periods for market price

***Result 3*: Participants reveal coherence problems when taking their decisions in *with* sessions.**

In the previous chapter we empirically addressed the question of a best-response behaviour in sessions with belief elicitation. Our analysis helped us to conclude that participants in a five-members market only asymptotically choose a quantity best-respoding to their price forecast. Additionally, our results proved that having two simultaneous decisions to take was a major element of difficulty and perturbation for participants; that encouraged us to run sessions where only one decision has to be taken. We thus check for instantaneous coherence in participants decisions in *with* sessions, by running for all participants a regression introducing the individual production as an explained variable and past, current prices, past

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[9] see previous chapter for the construction of the convergence intervals.
[10] Mann-Whitney test ($p>0,05$)

total output, as well as individual price forecast as explanatory variables, in order to clarify chapter 6 results. We estimate the parameters of the following regression:

$$q_{it} = c + ap_{t-1} + bp_t + dq_{-it-1} + \alpha ep^e_{it} + fq_{it-1} + \varepsilon_{it},$$

where $c$ is a constant term, $q_{it}$ is the individual production of subject $i$ in period $t$, $p_{t-1}$ and $p_t$ are former and current prices, $q_{-it-1}$ is the total production of the other members in $i$'s group in the last period, $p^e{}_{it}$ is the individual forecast of subject $i$ in period $t$ and $\varepsilon_{it}$ is a white noise term; $\alpha$ takes the value 1 if the subject participates in a *with* market and 0 if the participants belongs to a *without* market. We focus our attention on parameter $e$ that we expect to be significant, and when this constraint is fulfilled, we try to explain particular values that this parameter takes. We therefore present in table 7.8 aggregate results on the value of parameter $e$. This table reports information about the sign and significance of $e$, by accounting the number of participants in each category. The line "+" accounts in each treatment the number of participants with a significant positive parameter $e$; the line "-" accounts the number of participants with a significant negative parameter $e$; the line "/" reports participants with a non- significant parameter $e$.

| | *fast* | *slow* | *divergent* |
|---|---|---|---|
| + | 1 | 1 | 1 |
| - | 25 | 24 | 19 |
| / | 4 | 5 | 10 |

Table 7.8. Sign and significance for the $e$ parameter in *with* sessions

This tables indicated that less than 14% of the participants in fast sessions, 17% in slow sessions and 34% in divergent sessions do not correlate at all production decisions and price forecasts. For the majority of the participants, the two decisions are negatively correlated; this is a proof of consistence in decisions: participants understand that their production decisions, if they were to be replicated by the other members, would have an effect on price. Therefore, they do not stop at a myopic level of decision, which corresponds to statement: I think the price will be high, therefore I produce a high quantity. Instead, they enhance the eductive reasoning in a negative feedback environment, by understanding that the more (less) they produce, the lower (higher) will be the price. The average correlations between production and forecast per treatment are therefore of -0.28 (fast), -0.45 (slow) and -0.31 (divergent). But correlation does not necessarily imply causation in any meaningful sense of that word. We check for Granger causality between production decisions and price forecasts. The Granger approach to the question whether the production decisions (the forecast) causes the price forecast (the individual production) is to see how much of the current forecast (production) can be explained by past values of the individual production (forecast) and then to see whether adding lagged values of production (forecast) can improve the explanation. The forecast for example is said to be Granger-caused by the production, if the production decision helps in the prediction of the forecast, or equivalently if the coefficients on the lagged production's are statistically significant. Two-way causation is frequently the case; production Granger causes forecast and forecast Granger causes production[11]. Granger causality measures precedence and information content but does not by itself indicate causality in the more common use of the term. We compute two-way Granger causality test by picking a lag length of 10 periods (that corresponds to reasonable beliefs about the longest time over which participants could remember strategies). The null hypotheses being tested are that production does not Granger-cause forecast and that forecast does not Granger-cause production. Output from the test gives the relevant F-statistics for these two hypotheses. We therefore test 60 null hypotheses per treatment (2 for each subject, as explained before). We report in table 7.9. the percentages (out of 30) of rejection of the hypothesis in each treatment.

| Null hypothesis | *fast* | *slow* | *divergent* |
|---|---|---|---|
| *price forecast does not Granger cause individual production* | 23.3% | 40% | 30% |
| *individual production does not Granger cause price forecast* | 23.3% | 23.3% | 26.6% |

Table 7.9. Percentages of rejection of the null hypothesis

The fact that only about 1/3 of the participants decisions can be interconnected this way allows us to conclude that in sessions with beliefs elicitation participants are not fully coherent.

[11] It is important to note that the statement "the production Granger causes the forecast" does not imply that the forecast is the effect or the result of the production.

***Result 4*: In *without* sessions, subjects only weakly adopt the eductive-type of reasoning.**

As pointed out previously, eductive reasoning provides the same sequence of market price or output values as evolutive reasoning. Therefore, eductive reasoning is hard to test directly and we rather choose to search for violations of eductive reasoning. As eductive reasoning is an inherently sophisticated process, we first address the issue of the existence of simple rules that participants could follow when taking their decisions. If such simple rules were to be discovered in the structure of market prices, we could conclude that participants do not put into practice eductive reasoning because the market in which they evolve is predictable by the use of simple computations.

Therefore, to get a further insight into the market predictability, we investigated the characteristics of the market price series. Do these series incorporate a trend or structure helping subjects to forecast the price for the next period and to correlate their production decisions with that forecast in order to perform better? To answer that question we analyse for each group and each treatment the autocorrelation structure of market prices. The results are extremely suggestive. With few exceptions, for the treatments with elicitation, there is no price pattern easily exploitable by the subjects. When regressions are conducted with the 10 firsts lags, very few lags are significant and we cannot observe a regular lag structure.

In figure 7.2 we report the results for 6 selected groups which were involved in treatments with belief elicitation. The first 3 groups are of *fast* type and the 3 last of the *divergent* type.[12](see Appendix for all treatments).

Figure 7.3 shows the results of the same analysis for selected groups in treatments *without* belief elicitation. The figure clearly shows that for treatments "without" most of the first lags are significant; it also shows a regular structure of lags (decreasing significance). It means that in these treatments subjects use very simple forecasting rules for the market price when they have to take a production decision, i.e. they make a mix between past values of the market price and this pattern is easily exploitable by all the players.

Some other researches have shown (Croson, 2000) that players choose with more strategic sophistication when prompted to predict the issue of their actions. In without treatments, by using simple rules, subjects choices do not support the eductive hypothesis.

[12] The lines in the plots are the two standard error Barlett bands at 2,5% significance level

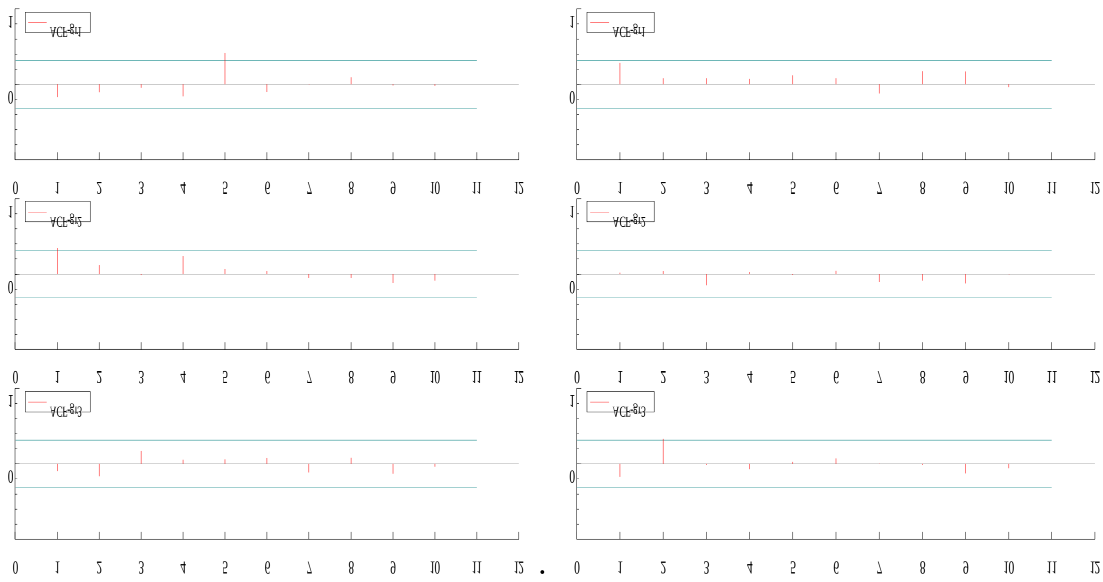


Figure 7.2. Autocorrelation for treatments with belief elicitation for 3 selected groups of the fast treatment (left) and 3 groups of the divergence treatment (right)

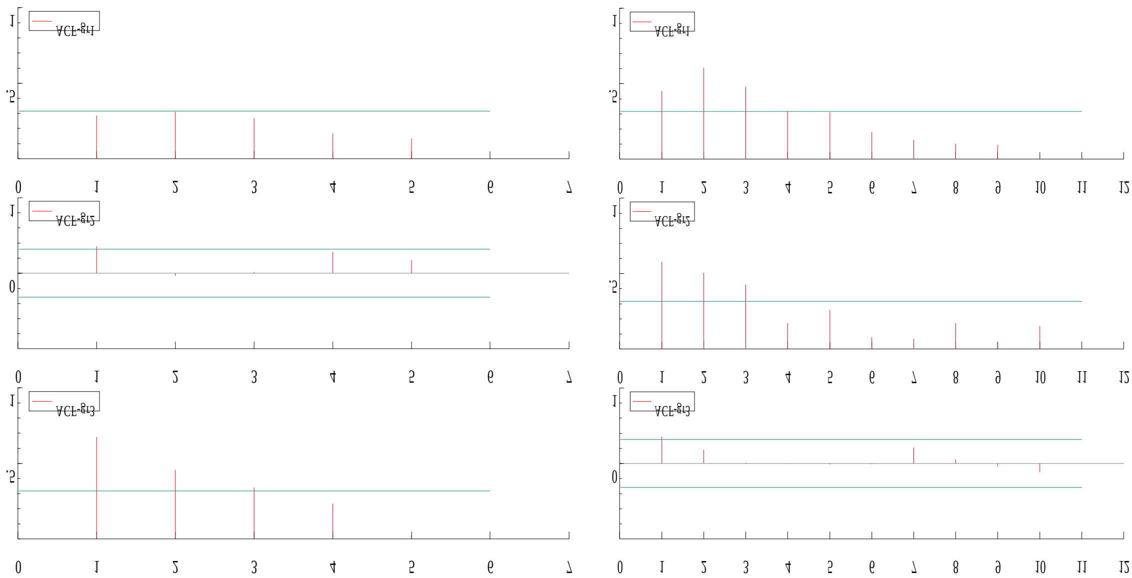


Figure 7.3. "Without" autocorrelation in treatments fast and divergent

Second, as eductive reasoning should not lead the participants to good (or simply) positive earnings in the divergent case, independently of the elicitation task, we have a look at the evolution of output profits in the divergent case. One of the implications of the eductive reasoning is that, in the divergent market, participants' task should become more and more difficult, as the application of the eductive reasoning leads to an explosive market where positive profits are difficult to maintain. Therefore, if subjects apply the eductive process, their output earnings should decrease with time.

Table 7.8.(a) presents the evolution of average earnings in the divergent groups over time. We present results for the first part of the experiments (periods 1-20) and for the second part of the experiment (periods 21-40) and table 7.8.(b) the averaged the result averaged over all groups.

| | | *gr1* | *gr2* | *gr3* | *gr4* | *gr5* | *gr6* |
|---|---|---|---|---|---|---|---|
| *With* | Periods 1 to 20 | 1033 | 927 | -568 | -1629 | 823 | 762 |
| | Periods 21 to 40 | 917 | 719 | 709 | 1138 | 844 | 552 |
| *Without* | Periods 1 to 20 | 909 | 1000 | 942 | | | |
| | Periods 21 to 40 | 611 | 900 | 783 | | | |

(a)group by group

| | | divergent | |
|---|---|---|---|
| | | *with* | *without* |
| Periods 1 to 20 | $\overline{\pi}_q$ | 224 | 950 |
| | $\sigma$ | 6079 | 385 |
| Periods 21 to 40 | $\overline{\pi}_q$ | 813 | 765 |
| | $\sigma$ | 720 | 302 |

(b)average

Table 7.10. Average earnings in divergent groups in periods 1-20 and 21-40

This description of the output profits evolution allows us to detect an opposite result on the validity of an eductive-type of learning. In half of the *divergent with* groups, average output profits in the second part of the experiment are higher than the corresponding profits in the first part of the experiment; for one group the presented values reveal a flat evolution and, for the two residual groups, a huge increase in output profits is detected. On average (table b), output earnings increase between the two parts of the experiment. This is the sign that the eductive reasoning is not put into practice in these groups and that participants experiment another type of reasoning allowing them to improve their earnings. In contrast, *divergent* *without* groups present another figure: earnings decrease as time goes on. This result will be enforced later by an additional analysis that we will provide in order to test $H_2$. Therefore, we make the assumption that the simple rules that participants put into practice in *without* groups, as shown before, are disconcerted by the persistence of the eductive reasoning contained in the environment structure (as we showed in the first part of this thesis): a negative feedback environment favours the type of eductive reasoning; this environmental influence is slightly perturbed by the complexification of the guessing task in treatments with beliefs elicitation, but still holds in treatments *without*.

***Result 5*: Elicitation doesn't improve convergence to REE and earnings.**

Table 7.3 presented several others interesting features. Comparing sessions with belief elicitation to sessions *without*, we observe that the average output profit is always larger in sessions *without* and the variability is smaller. These observations in contradiction with $H_5$ are very surprising, since belief elicitation was supposed to favour coordination among subjects and increase their output profit. Does it mean that without belief elicitation, subjects are actually better forecasters? It could be the case that belief elicitation adds an element of complexity or confusion for the subjects. Instead of facilitating their production decision, this additional prediction task could have increased the difficulty because they do not necessarily connect their production decision with their forecast.

Table 7.10. reports the average profit increases for all treatments ($i_{j,k}$). These rates are calculated as follows:

$$i_{j,k} = \frac{\overline{\pi}_{q\ (21-40),j,k}}{\overline{\pi}_{q\ (1-20),j,k}},$$

where $j = \overline{with, without}$ and $k = \overline{fast, slow, divergent}$.

The rate is larger than 1 except for treatment *divergent without*. It is also clear from the table, that belief elicitation has a stronger impact on profit increase than in treatments without. The fact that the rate of increase is larger for treatments with belief elicitation is in accordance with hypothesis $H_4$ and supported by a Wilcoxon ranked sum test ($p<0,05$). Average rates for the *without* treatments are close to 1 exhibiting low learning. But the difference in the rates could be due to the fact that starting profit levels are low in the *with* treatments and therefore there is much larger growth potential than in the *without* treatments.

| Belief elicitation | Yes | No |
|---|---|---|
| *Fast convergence* | 1,28 | 1,14 |
| *Slow convergence* | 1,15 | 1,10 |
| *Divergence* | 3,62 | 0,8 |

Table 7.11. Average growth rate of output profit per treatment

As for earnings, we observe a large change in variability between the two time intervals in groups with belief elicitation. The sharp reduction in variability suggests a strong learning effect in these groups. In contrast, variability is reduced to a much lesser extent in groups without belief elicitation where subjects seem to have adopted a much more cautious behaviour from the beginning of the market.

In the divergent case, the average profit level is much lower than in the two other treatments, in both time-intervals and whether beliefs are elicited or not. However, the evolution of the average profit level shows as in the two other treatments, a convergence of the profit as time evolves, around 900. This reveals that subjects were successful in coordinating their output choices, although they coordinated on a low level of profit. Since the divergence case stands in obvious contradiction with eductive learning, is must be the case that subjects were able to coordinate by relying on a rule which differs from sophisticated reasoning.

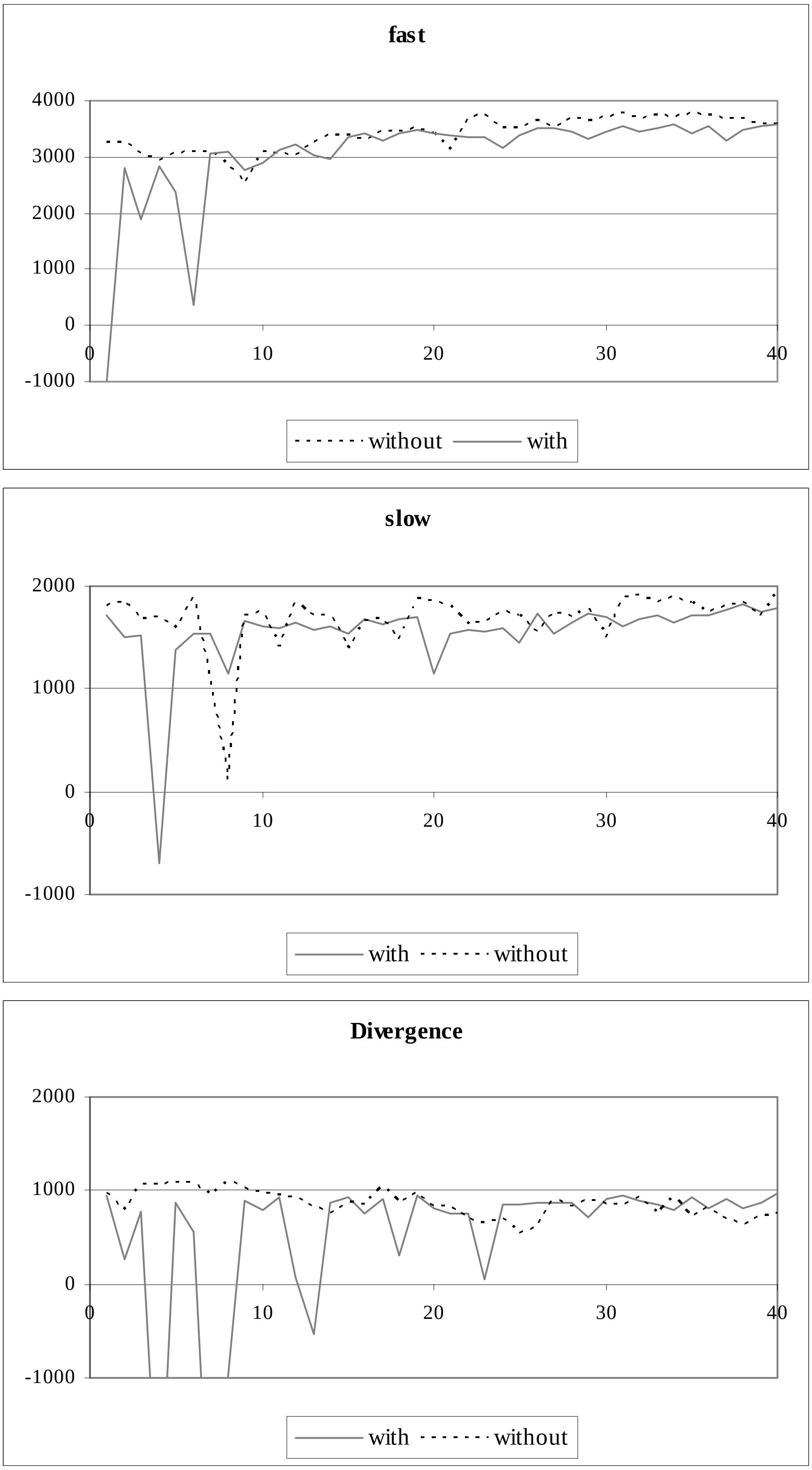



Figure 7.4.Evolution of average profits.

### 7.5. Synthesis and conclusion

The experiments presented in this chapter were intended to study the evolution of coordination and convergence towards equilibrium in a simple cobweb market environment when beliefs are (not) asked explicitly to subjects and rewarded according to a quadratic scoring rule. When analysing the data, we tried to address 5 main hypotheses: the *learning* hypothesis *($H_1$),* the *coordination* hypothesis *($H_2$),* the coherence hypothesis ($H_3$), the *eductive* hypothesis ($H_4$) and the *elicitation* hypothesis *($H_5$).*

Our analysis clearly support hypothesis $H_2$, we thus conclude that all groups are able to coordinate and there is not a clear difference between *with* and *without* groups. We observe convergence towards a price slightly above the Rational Expectation Equilibrium price in almost all treatments and groups.

Belief elicitation does not seem to improve the convergence process, but on the contrary to add more noise in early periods of the market. However, belief elicitation seems to improve subject's learning ability. Thus the evidence on hypothesis $H_1$ is more mitigate: all groups are able to learn, except for the divergent ones, and *with* groups have an important learning potential.

Our results seem to only partly confirm the assumption that subject's behaviour might be described by iterated elimination of dominated strategies (eductive reasoning, $H_4$). Experimental subjects in *with* treatments clearly adopt sophisticated rules when forecasting prices, and these rules could be assimilated to eductive reasoning. In contrast, experimental subjects in *without* treatments seem to adopt simple rules, such as expecting the next period price by looking at past realized prices. Because most subjects adopt such simple rules, belief coordination becomes very efficient, and fast convergence to a narrow price interval is observed in many groups and treatments. *Divergent* groups seem clearly to avoid the eductive reasoning leading them to chaos and reach coordination by other learning rules.

As for our main hypothesis $H_5$, the support provided for the other hypotheses does not allow us to clearly reject the assumption of equivalence of treatments *with* and *without*. Experimental subjects in treatments *with* have a better learning potential, but a lower initial efficiency point. They are able to use sophisticated learning rules, but reach coordination in the same asymptotic conditions as the *without* subjects.

**Contents**

# Chapter 8

# When vicious circles may turn virtuous: an experiment on a circular cobweb economy

## 8.1. Introduction

We described in chapter 5 the eductive reasoning process in a cobweb economy; in chapters 6 and 7 we aimed at investigating its dynamics in some experimental cobweb markets. Two of our main findings were that, firstly, larger groups perform better in the eductive reasoning, and, secondly, task multiplicity decreases the sophistication ability on one particular decision. The first conclusion deals with group inconsistency; the second is the consequence of self incoherence. In this chapter we are concerned with a new design that intends to remediate to both problems. The first problematic behaviour is defined as a mix of strategic behaviour and the self-serving bias investigated by Kaplan and Ruffle (2000). In small markets, participants experiment the "market-maker syndrome": they are aware of their market power and tend to take production decisions in order to preserve the price confirming their expectations. When doing so, they assume that the others will not change their productions and will not influence the market price. But as they all reason in this way, the market price is driven in the opposite direction. Therefore, they all make forecast errors in the same direction. In large groups, participants neglect the strategic possibilities of the other participants involved in the same group and they fail to accurately forecast "the forecast of others", i.e. they do not seem to be aware of group membership (they are better at hitting the REE, but more dispersed around the group average). Therefore we need to introduce stronger connexions into a group and transform the market-makers into price-takers. The second problematic point is that instead of strengthening beliefs coordination, the additional forecast task increases the complexity of the experiment and does not improve the convergence to the REE. Van de Velden and al. (2000) imagined an expectation driven market where participants have to accomplish only one forecast task and no trading occurs. Other research, for example the experiments from our previous chapter, was only focused on the production task. As our main research question is related to the eductive reasoning, it is still useful to ask experimental subjects to state their beliefs. Therefore, our experimental subjects have to state their beliefs about the price, i.e. to forecast the price imposed by the others for their production. In addition to this forecasting task, our experimental subjects are also involved in production decisions. Production decisions that they take determine the price in adjacent markets. Therefore, the activities related to production have a dual role: first, the individual production will be sold at an imposed price. The agent thus has to base his production decision on his price forecast. In this case the production should be determined by the price forecast. Second, the individual production will be aggregate in adjacent markets and will determine the price for the other subjects. In this case, the production decision introduces the interdependences in the economy, i.e. the circularity operator.

Our economy may be described as follows. There is a population of $n$ agents involved in a series of interactions, specified by a network. The network is defined, at any given point in time $t$, by a population of nodes (or agents) and by a set of links. Two types of interactions connect agent $i$ and agent $j$ across a link $ij$: a production link and a supervision link. The supervising link characterizes an asymmetric local interaction within a specific market, because the supervisor and the producers do not play the same role. The production link restores the symmetry at the scale of the economy (within all markets coexist) because through the production decision each agent has a double role (within a market he is price-taker and in all other markets he contributes to the determination of the price).
Therefore, any $n$-1 agents are linked by production links in that sense that they participate in a market where they are producers. The price determined in the $n$-1 agents group by the trade of the total production is imposed to the $n^{th}$ agent, who also has to forecast it. We call the link that is established between the $n^{th}$ agent and the group of the others $n$-1 agents a (double)supervision link in the sense that the $n^{th}$ agent has to supervise the market in order to make a (good) forecast of the price and the $n$-1 agents group supervises the $n^{th}$ agent by imposing him the price. Therefore any agent $i$ is linked to the other agents across two links: production and supervising, and has two roles, i.e. producer and supervisor; $n$ markets are active in the economy and settle on $n$ prices, each of them being forecasted once.

We call such a network, with circular interdependences, by an extension of language, a vicious circle[1]. We preserve from the original definition[2] the circularity operator and adapt it as follows: we will talk of the market environment as a vicious circle when an action is interconnected by a chain of circular circumstances to the other actions within an infinite oriented iteration revision process. The basic definition of a vicious circle does not apparently allow for any tendency to a state of equilibrium: this system of events has feedback loops reinforcing each iteration of the circle and therefore this circle will continue in the direction of its momentum until an exogenous factor intervenes and stops it. We follow here the analysis of Antonelli (1998), who proves that in such a system the circularity operator yields to a fixed point by a particular revision process (the vicious circle becomes virtuous). Let us remind that we demonstrated in Part I that a negative feedback environment favours the eductive reasoning; as eductive reasoning occurs in steps, we put into practice in this chapter an additional characteristic of the environment, i.e. the circularity, favouring the occurrence of higher and higher sophistication steps leading to the REE (fixed) point.

Therefore, the important question that will be addressed in this chapter is: *in presence of circular interdependences, guaranteeing the dynamic of the reasoning process, is participants ability to put into practice the eductive–type of reasoning improved?*

This chapter is organized as follows: section 8.2 describes the experimental design; section 8.3 presents the main results on these experiments and a discussion. Concluding remarks are given in section 8.4.

## 8.2. Experimental design

An economy is composed of $N$ markets, one market per subject. For subject $i$ ($i$=1,..,$N$), the price is determined by the aggregate output of the $N$-$i$ agents. Each participant $i$ in the experiment acts thus as a price-taking seller who has to forecast the price. The price is determined by the aggregate output of the $N$–$i$ participants, on which $i$ has no direct influence. We consider a simple economy with a perishable good produced at the beginning of a period and sold at its end. At each round of the experiment participant $i$ is asked to

[1] A vicious and a virtuous circle only differ by the fact that a virtuous cycle has favourable results and a vicious cycle has deleterious results.

[2] Originally, a vicious circle is defined as either a situation in which the apparent solution of one problem in a chain of circumstances creates a new problem and increases the difficulty of solving the original problem, or a condition in which a disorder or disease gives rise to another that subsequently affects the first, or finally a fallacy in reasoning in which the premise is used to prove the conclusion, and the conclusion used to prove the premise.

predict the price he expects and to take a production decision. His prediction has no effect on the market price. With *n* participants in the economy, subject *i*'s production decision is aggregated in *n*-1 markets. Any group of *n*-1 agents determines a price. At each period a participant is price-taker and forecaster in his own market and participates as producer in other *n*-1 adjacent markets. His production in all neighbourhood markets, together with other productions, is only used to determine the price. The only market where his production is actually sold is his own market.

Participants have common knowledge about their production costs, about the demand function, about their homogeneity and about the particular structure of the economy. All information about functions is given in tabular form (see Appendix). Economies' structure is fixed during the experiment: we employ a partner design. The experiment lasts for 40 periods. At each period each participant has to take two decisions, a production decision and a price forecast. Participants are rewarded for their production decisions and for the accuracy of their forecast. With usual notations, participant *i*'s earnings in period *t* are given by the sum of the output profit ($q_{it}\, p_{N-it} - CT(q_{it})$) and the forecast gain $1000 - 0.8(p_{N-it} - p_{it}^{e})^2$:

$$\pi_{it} = q_{it}\, p_{N-it} - CT(q_{it}) + 1000 - 0.8(p_{N-it} - p_{it}^{e})^2$$

The price $p_{-it}$ is calculated as $\dfrac{A - \sum q_{N-it}}{B}$ and the total production cost is given by $CT(q_{it}) = \dfrac{q_{it}^2}{2c} + dq_{it}$. Notations are the same as in previous chapters. Since we want to compare results of this experiment with our previous results, we will set the parameters at the same values as in previous chapters.

The experiment was entirely computerized through a Visual Basic interface (Bounmy, 2003) and took place in the LEES laboratory in Strasbourg in August 2003. We conducted three sessions, with three cohorts of 18 participants (one cohort per session) for a total of 48 inexperienced subjects recruited from various disciplines in the universities of Strasbourg. At the beginning of the experiment, subjects received paper copies of the instructions. Once that every subject finished reading them, they were also read aloud by the experimenter, in order to make sure that the rules were common knowledge among participants. Subjects were separated and could not communicate with each other. Each cohort of 18 subjects was split into three totally independent parametric-identical economies of six participants each, remaining fixed during the 40 interaction periods. Parameter values differed between cohorts: we investigated the *fast*, *slow* and *divergent* cobweb conditions listed in previous chapters. Because of the particular structure of the economy explained earlier, each economy condition (*fast, slow, convergent*) consisted of six markets, one market for each of the six subjects.

Each session begun with two trial periods in order to familiarize subjects with the graphic interface. The subjects' understanding of the instructions and procedures was checked by a short computerized questionnaire submitted before the beginning of the experiment. At the beginning of the experiment, each subject was endowed with 10 euros in points. Earnings (losses) gained (suffered) in each period are added (subtracted) to (from) the initial endowment. At the end of each period, each subject was informed about his own market price, the total quantity produced by the other members of the group, his production cost, his profit or loss and the remaining capital. Furthermore, subjects could see at any time their past data by clicking on a *history* button. Each subject within a market (a group) was indexed by a letter: A, B, C, D, E or F. Upon deciding on the quantity to produce and on a forecast, the market price was not known. The individual marginal and total cost were presented in a tabular form, in discrete (integer) units. This implies, as previously described, the convergence towards the REE in a finite number of eductive iterations. *B,* the slope of the demand function is held fixed, and we vary the slope of the supply curve, *C* (we consider a small value and a large value and an additional treatment with $B – C < 0$). Table 8.1 summarizes the parameter values for the different treatments. These parameters are the same as in previous chapters.

| | *fast* | *slow* | *divergent* |
|---|---|---|---|
| *A* | 900 | 900 | 900 |
| *B* | 9 | 9 | 9 |
| *c* | 1/10 | 8/5 | 21/5 |
| *C* | 5/10 | 8 | 21 |
| *d* | -660 | 15 | 300/7 |

Table 8.1. Parameters of the experimental treatments

The demand function was identical for all treatments and defined on { 0,1,…900 }. It was made clear to participant *i* that the total output taken into account for the establishment of his market price was the sum of all outputs in a group, excepting *i*. All possible choices for the total output are divided into 21 homogeneous intervals of amplitude 45 units. Each interval of total output determines a price (therefore prices could be 0, 5, 10, 15, …,etc). The maximum price is obtained for a zero demand and it is equal to 100.

Each session lasted one hour and a half; subjects earned 20 euros on average.

## 8.3. Experimental results

The fundamental activity of subjects in this experiment is forecasting. The dual role of the production activity creates interdependences and thus the production task is a basis for the circularity operator. Therefore, we concentrate mainly our analysis on prices and forecasts in this section. We present the experimental results as observations. Each observation is supported by a comment.

***Observation 1***: **Prices are stationary around REE and exhibit small volatility.**

In figure 8.1(a,b,c). we report the observed market prices, together with the REE value (60), in one *fast*(a), one *slow*(b) and one *divergent*(c) economy ( a cohort). The additional graphics on the other four cohorts are in the Appendix. As can be seen from the plots, all prices oscillate around the REE value. Results for the unit root tests ate given in the Appendix and confirm price stationarity.

***Observation 2***: **No strategic effect is detected, even at the beginning of the experiment.**

In *fast* and *slow* markets, the price volatility is very low (additional numerical results for this statement are given in Table 8.2.). In divergent markets, price volatility is higher, but prices still remain in the neighbourhood of the REE value. Let us recall that in chapter 6 price volatility was significantly higher on average in all treatments. We measure the price volatility by the standard deviation. We denote by $SD_{basic}$ the standard deviations that we reported in Chapter 6. We denote by $SD_{circular}$ the standard deviations that we report in table 8.2. We test the hypothesis $SD_{basic} - SD_{circular} > 0$ and we find that we cannot reject it at a 10% level. We interpret the price behaviour as good news about the effect of this particular design, more successful in hitting the REE than the previous.

Price series are stationary and this is verified on the periods at the beginning of the experiment, implying that any strategic behaviour is eliminated: prices do not converge, as in previous chapters, from above, to the REE (no underproduction). This observation is supported by the calculation of the number of reversals[3] in the price series for the first ten periods. No convergence from above is detected when a sequence of the type $p_1>p_2>\ldots>p_{10}$ is incomplete ($p_i$ is the market price for period $i$).

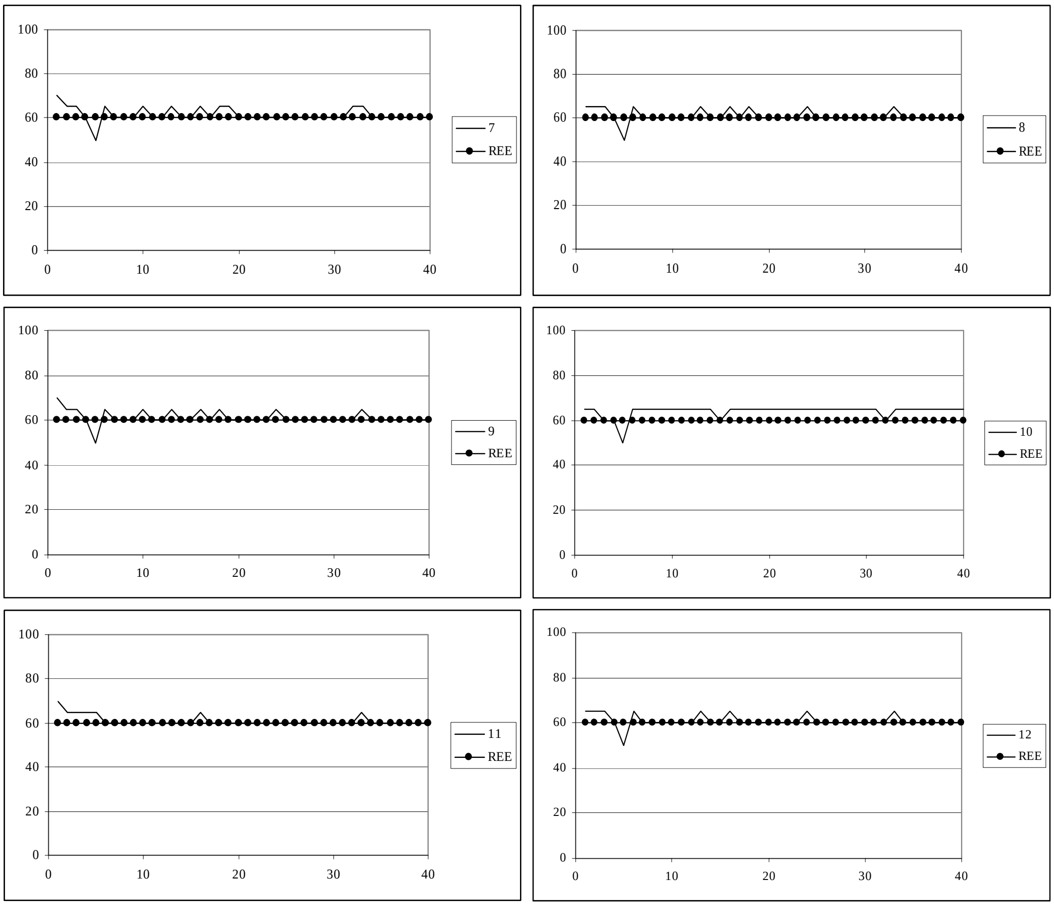



Figure 8.1.(a)Price history for one fast economy (each graph reports the price in a market)

***Observation 3*: Price series are very similar and display high correlation coefficients**.

As expected, the appearance of co-economy market prices is very similar; for example, in *fast* markets, we observe this slightly decrease in prices in period five in all markets except one; in *slow* markets the same oscillations (same moment same amplitude) occur in all groups; in *divergent* markets the price collapses occur at the same period and we observe the same trend in price evolution toward the end of the experiment. These observations indicate that the circularity operator works: when we calculate the mutual prices correlations in an economy, we find price series correlation coefficients between 0.64 and 0.76 under the fast

[3] A reversal is a situation in which for example $p_1>p_2$ and $p_3>p_2$.

condition; 0.58-0.66 in the slow economies; 0.59-0.82 in the divergent setting (correlations higher that 0.7 represent about 57% of the correlations).

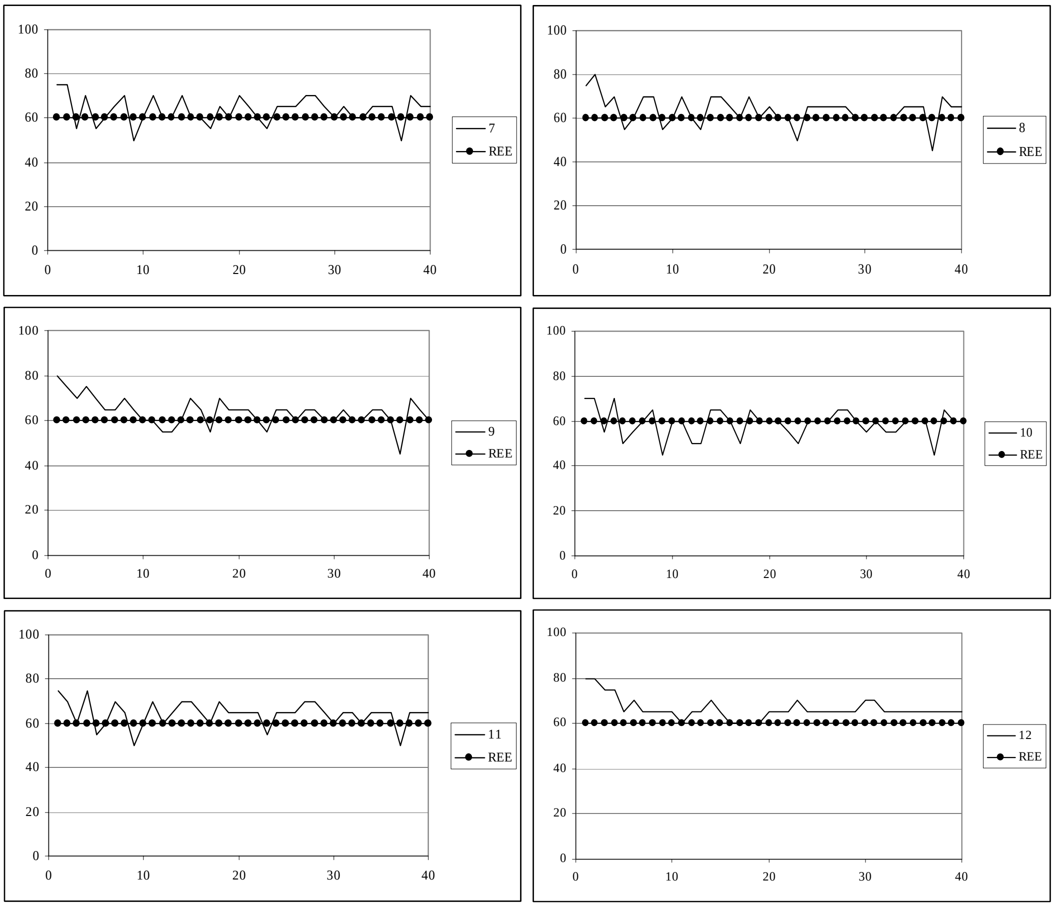



Figure 8.1.(b) Price history for one slow economy

***Observation 4*: Participants forecasts are almost confounded with the price series.**

Chaotic behaviour that we should expect according to the theory on eductive reasoning is not detected under the divergent condition. But as in the two convergent conditions price evolution is very flat, we can consider our results as very sensitive, and in that case, price evolution in the divergent case displays higher oscillations than in the convergent treatments. Therefore, the results obtained in the divergent case are not alarming: the circularity operator is supposed to strengthen the interdependences between subjects' behaviour and helps perpetuating the current reasoning. The eductive reasoning can be strengthened only in markets where it is implemented. In other situations, other types of reasoning are used.

In table 8.2 price statistics, together with statistics on forecasts, are presented. At a 5% signification level, we cannot reject the hypothesis of equality between prices and forecasts (on average). To have a deeper insight, we examine the forecast earnings of the participants, that inform us about the exact quality of predictions. Results are given in table 8.3.

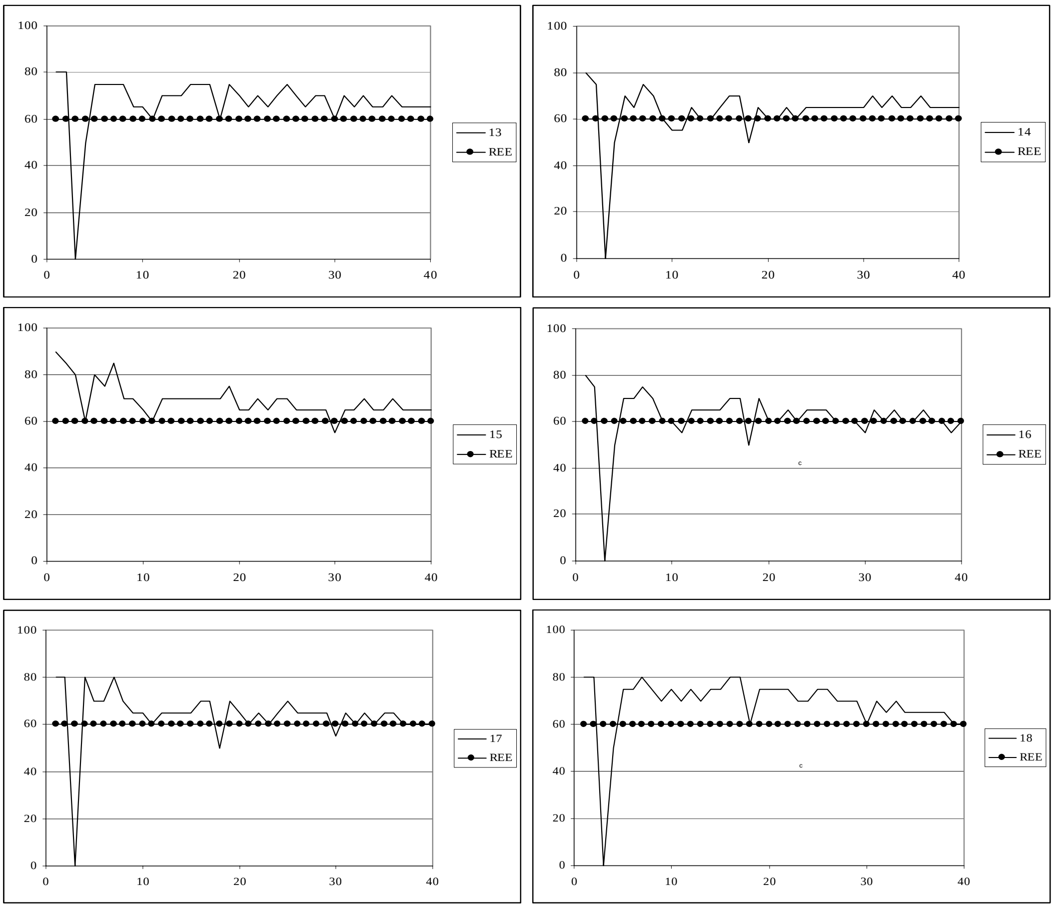



Figure 8.1.(c) Price history for one divergent economy

The quality of the participants' forecasts can be better judged by the inspection of the forecast earnings in the table 8.3. The first line results in table 8.3 reports forecast earnings in each treatment averaged over all participants and first 20 periods. Second line presents average forecast over the last 20 periods of the experiment. Average forecast earnings in this experiment are significantly higher (at a 5% significance level) than the corresponding values in the experiment presented in chapters 6 and 7(see table 6.5 in Chapter 6). They increase between the first and the second part of the experiment and a huge decrease in standard deviations is observed between the two subperiods. This is a proof that, in this experiment, participants are very good forecasters; especially in the second part of the experiment, their forecast is confounded with the realized market price (perfect forecast) in more than 90% of the situations and this is common behaviour (standing for coordination, as $\sigma$ is very low).

| **price** | ***fast*** *m* | *σ* | ***slow*** *m* | *σ* | ***div*** *m* | *σ* |
|---|---|---|---|---|---|---|
| ***1*** | 65.3 | *2.8* | 63.3 | *5.9* | 60.6 | *7.7* |
| ***2*** | 66.3 | *3.7* | 62.5 | *5.3* | 59.1 | *7.4* |
| ***3*** | 67.0 | *4.6* | 62.3 | *5.8* | 64.8 | *7.1* |
| ***4*** | 65.1 | *1.8* | 62.0 | *4.6* | 60.8 | *8.2* |
| ***5*** | 66.1 | *4.2* | 65.9 | *5.6* | 60.9 | *8.0* |
| ***6*** | 66.3 | *3.7* | 60.3 | *11.2* | 61.3 | *8.1* |
| ***7*** | 61.3 | *3.2* | 63.4 | *6.0* | 65.6 | *6.1* |
| ***8*** | 60.9 | *2.7* | 62.1 | *11.3* | 62.1 | *6.2* |
| ***9*** | 61.1 | *3.1* | 62.4 | *11.3* | 62.6 | *5.4* |
| ***10*** | 64.1 | *2.7* | 57.4 | *11.2* | 59.8 | *7.2* |
| ***11*** | 61.0 | *2.3* | 63.0 | *10.9* | 67.3 | *7.1* |
| ***12*** | 60.8 | *2.7* | 66.3 | *4.6* | 59.6 | *6.3* |
| ***13*** | 63.0 | *3.2* | 57.4 | *5.4* | 67.1 | *12.4* |
| ***14*** | 64.0 | *3.0* | 66.0 | *4.3* | 63.1 | *11.9* |
| ***15*** | 63.3 | *3.1* | 64.3 | *5.0* | 69.1 | *7.0* |
| ***16*** | 63.3 | *3.3* | 66.9 | *5.0* | 61.8 | *11.9* |
| ***17*** | 63.0 | *3.5* | 62.5 | *5.8* | 64.0 | *12.2* |
| ***18*** | 63.3 | *3.1* | 64.4 | *5.1* | 68.9 | *13.0* |

| **forecast** | ***fast*** *m* | *σ* | ***slow*** *m* | *σ* | ***div*** *m* | *σ* |
|---|---|---|---|---|---|---|
| ***1*** | 65.5 | *5.9* | 63,3 | *4,5* | 54,3 | *6,8* |
| ***2*** | 61 | *5.6* | 62,6 | *6,8* | 60,9 | *5,0* |
| ***3*** | 67 | *3.0* | 63,6 | *6,1* | 58,9 | *16,3* |
| ***4*** | 65 | *2.8* | 62,1 | *6,0* | 61,0 | *7,9* |
| ***5*** | 65.7 | *3.1* | 65,3 | *4,4* | 61,4 | *8,4* |
| ***6*** | 64.5 | *4.9* | 58,3 | *2,9* | 59,6 | *6,9* |
| ***7*** | 61.7 | *2.4* | 60,0 | *7,7* | 66,6 | *5,6* |
| ***8*** | 62.6 | *3.0* | 62,6 | *7,2* | 61,9 | *4,9* |
| ***9*** | 60.2 | *3.9* | 63,1 | *5,8* | 63,1 | *7,0* |
| ***10*** | 63.6 | *3.2* | 59,3 | *5,6* | 60,3 | *5,8* |
| ***11*** | 61.6 | *6.4* | 60,6 | *10,3* | 59,9 | *6,8* |
| ***12*** | 61.7 | *2.4* | 65,1 | *3,5* | 61,5 | *8,2* |
| ***13*** | 61.3 | *7.1* | 59,6 | *7,1* | 62,3 | *9,1* |
| ***14*** | 64.3 | *3.0* | 64,9 | *3,1* | 65,1 | *6,7* |
| ***15*** | 63.1 | *3.3* | 64,3 | *3,5* | 71,4 | *11,8* |
| ***16*** | 63 | *3.4* | 64,9 | *8,0* | 68,8 | *7,7* |
| ***17*** | 62.7 | *6.3* | 61,5 | *4,4* | 68,6 | *12,6* |
| ***18*** | 62.1 | *4.1* | 65,3 | *3,7* | 70,5 | *7,1* |

Table 8.2. Descriptive statistics for prices and forecasts

| | | *fast* | *slow* | *divergent* |
|---|---|---|---|---|
| Periods 1 to 20 | *m* | 960 | 955 | 790 |
| | *σ* | 84 | 66 | 465 |
| Periods 20 to 40 | *m* | 997 | 984 | 978 |
| | *σ* | 6,1 | 26 | 26,3 |

Table 8.3. Average forecast earnings

***Observation 5*: Participants take into account prices *and* individual production when forming their forecasts, to the extent corresponding to their sophistication ability.**

Participants are good forecasters. We are interested in how they form their expectations in such an environment. Remember that in a classic cobweb market as the one experimented in Chapter 6, participants did not best respond to their individual output when forming their price expectation. Production decision and forecasts were only slightly connected. With the circular economy that we investigate here, we aimed at inducing more connexions between the two decisions. The circularity operator that we introduced trough the production decisions is assumed to work as follows: the forecasting task should be based on an a priori computation in the beginning of the experiment (first period), subjects only integrating their asymmetric situation (they do not relate their forecast with their individual production decision) and announcing expectations that are not related to prices or production; the next step is for them to take into account the evolution of market price, through observation; but as the experiment proceeds, the circularity operator strengthens group interconnexions and induces coordination. Therefore participants will also take into account their individual production when forming their predictions.

We make the assumption that these steps will be followed by the participants and the circularity operator will make it possible for them to integrate the market price evolution but also individual production decisions in their forecasts. In order to test this assumption, we will perform the following analyses: we first evaluate the correlations coefficients between the two decisions that participants take and the realized market price and subsequently we calculate how much of the variations in forecasts are explained by any type of correlation.

We do find significant correlations between price and forecasts and between price and individual production: in absolute value and on average, correlation coefficients are larger than 0.5, but differences exist between participants. We thus report in table 8.4 the sign categories for the correlation coefficients between price and forecast and between forecast and production. We read the table as follows: the signs + and – in the first line correspond to positive and negative correlation respectively. The first sign in each pair corresponds to the correlation between price and forecast and the second sign to the correlation between forecast and production. For example +/+ means that correlations between price and forecast and between forecast and production are both positive.

| price-forecast/ forecast-production | +/+ | +/- | -/+ | -/- |
|---|---|---|---|---|
| *fast* | 5 | 7 | 6 | 0 |
| *slow* | 8 | 8 | 0 | 2 |
| *divergent* | 10 | 3 | 2 | 2 |

8.4. Correlation signs for price/forecast and forecast/production
(number of subjects out of 18)

Participants do not all have the same correlation profile; this is an information about the reasoning process that participants use when stating their prediction, and, more precisely, about the depth of their reasoning processes. If participants make use of an eductive-type of reasoning, they are likely to stop at different reasoning levels, according to their sophistication ability. According to the step of eductive introspection that participants use in the forecasting task, correlation between, for example, price and forecast, can be negative or positive (alternatively).

As additional evidence on this observation we compute the variance decomposition for each participant's forecast. As in this experiment each variable is designed to help understanding the others, we perform variance decomposition from a vector autoregressive estimation including each variable (price, forecast, production) together with its first lag. Variance decomposition calculates the standard errors for the price forecast at different horizons and gives the percentages of the variance due to specific perturbations. As an example, we present in table 8.5 the variance decomposition for one part participant in the *fast* treatment (other decompositions are in Appendix). The first column gives the standard error for a maximum time horizon equal to 10; the second column the percentage of the variance explained by variations in the market price; in the third and the forth columns percentages of variations due to forecast and individual production are reported. For this particular participant, between 60% and 82% of variations are explained by a process inherent to the forecast variable itself. With time, production starts explaining forecast variations, but only to an extent of 7% maximum. Changes in market price explain between 17% and 32% of the changes in forecasts.

| Variance Decomposition of PREV5: | | | | |
|---|---|---|---|---|
| Period | S.E. | PRIX5 | PREV5 | PROD5 |
| 1 | 2.37 | 17.58 | 82.41 | 0.00 |
| 2 | 2.57 | 19.83 | 78.47 | 1.69 |
| 3 | 2.72 | 25.76 | 70.32 | 3.91 |
| 4 | 2.83 | 29.42 | 65.10 | 5.46 |
| 5 | 2.90 | 31.19 | 62.46 | 6.34 |
| 6 | 2.93 | 31.96 | 61.24 | 6.78 |
| 7 | 2.95 | 32.29 | 60.71 | 6.99 |
| 8 | 2.96 | 32.41 | 60.50 | 7.07 |
| 9 | 2.96 | 32.46 | 60.42 | 7.11 |
| 10 | 2.96 | 32.47 | 60.38 | 7.13 |

Table 8.5. Variance decomposition for subject 5 in the *fast* treatment

We calculate all variance decompositions. In the *fast* treatment, for short time horizons, forecasts deviations are purely forecast driven (by specific computations, representing between 90% and 99% of the standard errors). For long time horizons, prices drive at most 58% of predictions deviations (and at least 4%), individual production at most 15% (and at least 1%) and forecasts themselves explain between 41% and 96% of the variance. This result stands for increasing sophistication in the reasoning process and coordination (circularity works and participants realize that everything is interconnected). In the *slow* treatment, short time figures present predictions deviations explained by at least 88% by forecasts and at most 7% by prices. Long run explanations include at most 15% effects of production decisions, 67% price deviations and between 32% and 86% forecast variation. A similar picture stands for the *divergent* treatment, with lower percentages for forecasts influence in the long run. We therefore conclude that participants make use of the circularity of their environment by slightly integrating into their forecast the coordination dimension, and each one of them performs this reintegration according to his computational ability.

## 8.4. Conclusion

In this chapter we built a new experimental environment in order to investigate expectation formation in a cobweb economy. In particular we investigated whether agents are able to better forecast prices (and to learn the REE price) in a market with a perpetuating eductive reasoning momentum. We constructed the economy by adding in the classical design of a cobweb market a circularity operator. This operator gives the environment the appearance of a vicious circle. All participants had to predict prices in their own market, as completely price takers (in order to eliminate any strategic behaviour), and the circularity was introduced trough production decisions: each individual production was aggregate in all remaining markets to establish other participants' prices. We find, firstly, that participants in these markets are remarkably good in reaching the REE price; that they do it collectively; that no strategic effect is detected in their production decisions; that they are almost perfect forecasters; that, finally, they assimilate coordination in their reasoning process and make the vicious circle to turn virtuous.

# General conclusion

In this thesis, we investigated the mechanism of the eductive reasoning in negative feedback situations. The contribution of this thesis was, first, to formalize these situations as beauty contest games, and second, to test them in a market environment. In both cases, we intended to asses the eductive reasoning ad its mechanism. By the means of beauty contest games we could identify several degrees of reasoning and several types of agents. In market situations, we analyzed the coordination, the price convergence and the stability of the equilibrium.

We demonstrated that the success in coordination and the stability of the equilibrium are determined not only by the eductive abilities of the agents, but also by the characteristics of the situation. Under the assumption of identical reasoning abilities, agents in different environments will experience different probabilities of success for their actions. We placed the agents in environments with complete information on the fundamentals, but uncertainty about the strategies of the others. The available information is understood and assimilated through a cognitive process. This process is favoured by the environment where it operates. Within a stabilizing environment, its chances to succeed are increased. We identified the negative feedback situations as stabilizing environments.

An agent can use a more or less complex cognitive process. We presented in Chapter 1 the eductive reasoning mechanism and we characterized the negative feedback situations. As the eductive process can be more or less complete, we associated it with several sophistication degrees or steps. Therefore we could measure the sophistication through steps and the reasoning depth through the number of steps used in sophistication. To switch from a step to another, the agents have to form iterative beliefs. Our question was about determining when and why the iterative reasoning process was likely to stop. We explained that this moment can be voluntary or involuntary determined. When the reasoning process was involuntary interrupted, the agent's eductive ability corresponded to the last reasoning step. When the reasoning process was voluntary interrupted, the agents selected the last reasoning step as the result of a benefit-costs analysis. An agent was likely to stop sophisticating because he estimated that his opponents would stop before or because he could identify a point starting on his reflective beliefs became intuitive and the information processing costs disappeared. We showed that with the introduction of the negative feedback situations, this point was likely to be reached after only a limited number of eductive steps. This is the consequence of the characteristics of a negative feedback situation, corresponding to the mental architecture of the communication activity and of the numbers treatment. In this way, useful information is repeatedly scanned.

In the remaining of this thesis, we formalized and experimentally tested these discussions in two parts. The first part corresponded to chapters 2 to 4 and the second part to chapters 5 to 8. In the first part, we presented the mechanism underlying the eductive reasoning through negative feedback beauty contest games. In the second part, we applied these games to cobweb markets.

First chapters from each part respectively were chapter 2 and chapter 5. In chapter 2 we mathematically presented our variant of the beauty contest game. In this game, several players had to choose a number within a closed interval, for example [0,100]. The winner was the player whose choice was the closest to a target determined by 100-$p\times$mean of all chosen numbers within a group. In particular, we presented the steps of the eductive reasoning, the isomorphism of this game with the basic beauty contest game and characterized its equilibrium. We also presented a review of the previous experimental literature listing all the modifications and analyses of the basic beauty contest game.
The previous experimental work on the cobweb markets was presented in chapter 5. Several cobweb markets have been previously tested, under different information conditions. We also described in this chapter the linear cobweb market, the eductive reasoning corresponding to

this market and the equivalence with the negative feedback beauty contest games. However, in the cobweb market, during the elimination of dominated strategies process, participants had to take a two-dimensioned decision: a production decision and a price forecast.

In the first part, negative feedback beauty contest games have been tested. In chapter 3, we run a one-shot experiment. Our results showed that in negative or feedback situations the same depth of reasoning is put into practice, but in negative feedback situations there is a higher propensity to reach the equilibrium. We simulated the effects of this propensity and found that the simulated repetition of the game starting from the initial configuration had lead faster to the equilibrium than in the traditional game.

In chapter 4, we verified this result and the influence of repetition on initial choices. We assumed that the repetition will better focalize the subject on his guessing task. The difference in the depth of reasoning was very small (in both chapters around 2 steps on eductive reasoning). We also showed that the useful information is higher in our games (we based our calculations the Shannon entropy criteria and on the psychological research on numbers perception). The reflective beliefs were transformed faster into intuitive beliefs because the equilibrium point is repeatedly scanned. This depended on the parameter *p*.

We tested cobweb markets in chapters 6 to 8. We investigated the stability of the eductive reasoning in linear markets and identified several factors likely to favour the eductive reasoning. In Chapter 6, we investigated the effects of the group size on the reasoning process. Subjects took part in treatments where they had to make two simultaneous decisions, in a repeated way: a production decision and a price forecast, remunerated respectively according to the rules of profit calculation or to their quality. The subjects were divided into small or large sized groups and the linear functions were transformed into step functions; according to the relative slopes of the supply and demand functions, convergence towards the equilibrium occured or not, and was more or less fast. Our results showed that simple forecasting rules could not be deduced from the price pattern and that production decisions and the price forecasts were not connected by a best-response relation.

In chapter 7, we particularly addressed the assumption that the elicitation of the beliefs improves convergence towards the equilibrium. We thus compared elicited beliefs sessions to non-observable beliefs sessions. We concluded that simple rules of behaviour can explain the choices in the treatments without beliefs elicitation and that the elicitation did not improve convergence and profits.

In order to reduce the strategic behaviours and to restore the coherence of the production decisions and price forecasts, we introduced into chapter 8 a circularity operator in the cobweb markets. A subject needed to forecast a price determined by the other members of the group; this was valid for any subject. We showed that, with time, the participants took into account the prices *and* their individual production when they formed their forecasts, a proof of their ability of sophistication and comprehension of the interactions of the economy.

In conclusion, our experiments shed more light on the decision-taking problem in negative feedback situations, when a sophisticated reasoning is used. We showed why such reasoning had more chances to succeed in negative feedback situations. We showed that the success of a strategy was related not only to the cognitive ability of the agents, but also to the stabilizing factors of the environment. Thus the agents better process the information and transform their reflective beliefs into intuitive beliefs in negative feedback environments. Their interactions result in stable situations. However, we acknowledge that all the elements of a decision-making problem are not taken into account. We deliberately chose to test the eductive reasoning in simple and stable situations. Moreover, the experimental work on beliefs measures is biased because the notional time is not directly observable. On the contrary, the issue of a reasoning process is observable through experiments. We observed the convergence processes in numbers choices and in the price series and their stability. We introduced in our thesis psychological elements.

Our experiments thus contribute to the experimental economics literature by the introduction of the negative feedback beauty contest games and by the description of the eductive reasoning in experimental cobweb markets. We showed that the rationality could be voluntary limited when reflective beliefs can be turned into intuitive beliefs.

At the beginning of this thesis, we emphasized that negative feedback beauty contest games had never been formalized and tested and that eductive reasoning has been shortly addressed in the experimental literature. Moreover, it seemed that in the real world, negative feedback situations were more stable than positive feedback situations. Our questions are now:

First, in the real world, the environments are multi-dimensioned and positive and negative feedback coexist. Would our results be valid within this framework?

Second, decision-making in real world is more complicated and environments are not stable Would the depth of reasoning be the same under shocks or in multiple products markets?

Third, the transformation of the reflective beliefs into intuitive beliefs depends on psychological focal points or on social influences. Therefore, we should construct psycho-economic experiments in order to detect these points and their influence.

Finally, these elements lead us to think that a global work should be done in order to understand all the complexity of the eductive reasoning.

# Conclusion générale

Dans ce travail, nous nous sommes intéressés à la mise en place du raisonnement éductif dans des situations de feedback négatif. Notre contribution a été, d'une part, de formaliser ces situations en tant que jeux du concours de beauté, et, d'autre part, de les tester sur une situation de marché. Dans les deux cas, l'objectif a été l'évaluation des capacités éductives des agents et de leur mécanisme de mise en œuvre. Dans le cadre des jeux du concours de beauté à feedback négatif, nous avons pu identifier des degrés de raisonnement et des types d'agents. Dans les situations de marché, nous avons examiné les conditions sous lesquelles ces agents se coordonnent, ont des stratégies qui impliquent la convergence des prix et la stabilité de l'équilibre.

Nous avons montré que le succès de la coordination et la stabilité de l'équilibre ne dépendent pas uniquement des capacités éductives des agents, mais aussi des caractéristiques de la situation. Ainsi, à capacité de raisonnement égale, des agents placés dans des environnements différents ont des actions dont les chances de réussite sont différentes. Nous avons placé les agents dans des situations dans lesquelles l'information sur les fondamentaux est complète, et la seule incertitude persistante concerne les stratégies des autres. L'information disponible est comprise et intégrée (transformée en connaissance commune) par un processus cognitif. Ce processus est favorisé par l'environnement dans lequel il opère. Si l'environnement est stabilisateur, le processus de raisonnement a plus de chances de réussir. Nous avons identifié les situations de feedback négatif comme des environnements stabilisateurs.

Le processus cognitif qu'un agent met en place peut être plus ou moins complexe. Ainsi, le Chapitre 1 présentait, d'une part, le mécanisme du raisonnement éductif et, d'autre part, caractérisait les situations de feedback négatif. Puisque ce processus peut être plus ou moins complet, nous l'avons associé à des degrés de sophistication : plus de sophistication implique un raisonnement plus poussé ou plus complet. Ainsi, la sophistication pourrait-elle se mesurer en étapes et la profondeur du raisonnement en nombre d'étapes. Pour franchir ces étapes les agents doivent former des croyances réflectives de manière itérative. La question qui se posait était à quel moment le processus de sophistication s'arrêtait et pour quelle raison. Nous avons mis en avant le fait que la séquence d'étapes du raisonnement éductif pouvait être interrompue soit involontairement, soit volontairement. Lorsque le raisonnement est interrompu de manière involontaire, la dernière étape franchie correspondait à la capacité cognitive de l'agent. Lorsque le raisonnement était interrompu de manière volontaire, la sélection de la dernière étape franchie était déterminée par un calcul avantages- coûts liés à la sophistication. Un agent pouvait s'arrêter de sophistiquer soir parce qu'il avait estimé que les autres allaient s'arrêter avant, soit parce qu'à partir de ce point il pouvait transformer ses croyances réflectives en croyances intuitives et donc faire disparaître ses coûts de traitement de l'information. L'introduction des environnements à feedback négatif nous a permis de montrer qu'il était probable, dans ces situations, qu'un nombre limité d'étapes de raisonnement soient nécessaires pour arriver à tenir des croyances intuitives. Ceci est du au fait que les situations de feedback négatif correspondent à l'architecture mentale du traitement des nombres et de la communication verbale. Ainsi, lors de la mise en œuvre des étapes du raisonnement éductif, les éléments qui constituent l'information utile sont scannés de manière répétée.

Nous avons choisi de formaliser et tester expérimentalement ces discussions en deux parties. La première partie correspondait aux chapitres 2 à 4 et la deuxième partie aux chapitres 5 à 8. Dans la première partie, le mécanisme du raisonnement éductif a été présenté et testé à travers l'introduction des jeux du concours de beauté à feedback négatif. Dans la deuxième partie, ces jeux ont été appliqués à des situations de marché de type cobweb.

Les chapitres 2 et 5 ouvraient chacune des deux parties. Ainsi, le chapitre 2 faisait-il une présentation mathématique complète de notre variante des jeux du concours de beauté. Dans ce jeu, les joueurs devaient choisir des nombres dans un intervalle fermé, par exemple entre 0 et 100, et le gagnant était la personne dont le choix était le plus proche de 100-$p\times$moyenne de tous les nombres choisis dans un groupe. En particulier, nous avons présenté les étapes du raisonnement éductif, l'isomorphisme de ce jeu avec les jeux du concours de beauté classiques (à feedback positif), et les caractéristiques de son équilibre. Une revue de la littérature concernant les jeux du concours de beauté a aussi été introduite dans ce chapitre. Cette revue a présenté toutes les modifications apportées aux jeux du concours de beauté à feedback positif et les différentes analyses des résultats.

La revue de littérature expérimentale correspondant à la situation de marché à feedback négatif (le cobweb) a été présentée dans le chapitre 5. Dans ces travaux, plusieurs marchés de type cobweb ont été testés, sous des conditions d'information sur les fondamentaux plus ou moins complètes. Nous avons aussi décrit dans ce chapitre le modèle cobweb linéaire et la mise en place du raisonnement éductif et d'autres règles de raisonnement dans ce chapitre. Ce modèle est mathématiquement équivalent aux jeux du concours de beauté à feedback négatif mais comporte deux dimensions : les prévisions de prix *et* les décisions de production individuelle doivent être prises en compte lors de l'élimination des stratégies dominées.

Dans la première partie, les jeux du concours de beauté à feedback négatif ont été testés expérimentalement dans les chapitres 3 et 4. Dans le chapitre 3, une version à une période de ce jeu a été testée. Les résultats ont confirmé notre hypothèse de départ, c.à.d. une égalité entre les profondeurs de raisonnement des participants dans tous les types des jeux du concours de beauté, mais une propension plus grande à converger vers l'équilibre dans les jeux à feedback négatif. Nous avons décrit les effets de cette propension à travers une simulation du jeu répété avec la même structure de population. Nous avons trouvé une convergence plus rapide dans le jeu à feedback négatif.

Nous avons expérimentalement reproduit le jeu à feedback négatif à plusieurs périodes dans le chapitre 4. Les buts de ces nouvelles expériences étaient de tester les résultats des simulations mais aussi de vérifier l'influence de la répétition du jeu sur les choix initiaux. Nous avons fait l'hypothèse qu'à travers la participation à un jeu répété dans des conditions identiques, les sujets expérimentaux pourraient se focaliser dès leurs premiers choix sur leurs stratégies. Nous avons trouvé une différence très sensible entre le degré de raisonnement de la population de chapitre 3 et la population du chapitre 4, autour de deux étapes de raisonnement éductif. Dans ce chapitre nous avons aussi montré que l'information utile dans le jeu à feedback négatif est plus grande que dans le jeu classique. Cette information a été calculée selon le critère de Shannon et compte-tenu de la représentation des nombres (l'effet SNARC).

De ce fait, l'équilibre était scanné plusieurs fois et les croyances réflectives deviennent intuitives plus rapidement. Cette transformation dépendait du paramètre *p* du jeu.

Les situations de marché de type cobweb ont été testées expérimentalement dans les chapitres 6 à 8. Dans ces chapitres, nous avons choisi de faire une investigation de la convergence et de la stabilité dans des marchés linéaires, et d'identifier plusieurs éléments qui seraient susceptibles de favoriser un raisonnement de type éductif. Ainsi, nous avons successivement choisi de mesurer les effets de la taille du groupe, de l'élicitation des croyances et de la circularité des interactions sur la convergence des prix vers l'équilibre. Ces trois facteurs stabilisent les croyances. Un autre facteur est pris en compte dans les marchés de type cobweb qui y sont testés : la vitesse de convergence. Elle est déterminée selon les pentes relatives des courbes d'offres et de demande et mesurée par le nombre d'étapes de raisonnement éductif nécessaires à l'obtention de l'équilibre. Comme nous avons utilisé des fonctions en escalier dans les protocoles expérimentaux, cette vitesse est finie. Nous avons testé un modèle de convergence rapide, un modèle de convergence lente et un modèle de divergence.
Dans le chapitre 6, nous avons testé ces modèles avec des groupes de 5 ou 10 sujets. Ces sujets devaient prendre deux décisions : une décision de production et une prévision de prix. Ils avaient connaissance commune des fondamentaux. Nous avons montré que les croyances sont coordonnées dans ce type de marché, mais pas nécessairement sur la prédiction théorique. Nous avons aussi trouvé l'évidence de la mise en œuvre d'un raisonnement sophistiqué de la part des sujets. Cependant, les prévisions de prix et les décisions de production n'étaient pas reliées par une relation de meilleure réponse.

Dans le chapitre 7, nous avons comparé des sessions dans lesquelles les sujets devaient prendre deux types de décision (production et prévision) avec des sessions dans lesquelles ils devaient seulement prendre des décisions de production. Nous avons montré que l'élicitation des croyances n'améliorait pas la convergence. En revanche, un résultat important a été le fait que des règles simples de prévision expliquaient les choix dans les sessions dans lesquelles les croyances n'étaient pas élicitées. Nous avons observé des comportements stratégiques chez certains sujets.

Ainsi le chapitre 8 tentait-il de réduire ces comportements et de réintroduire la cohérence entre les décisions de production et les prévisions de prix. Nous avons relié les sujets par une relation de circularité. Cette relation fonctionnait de la façon suivante : un sujet devait faire une prévision sur un prix qui était déterminé uniquement par les autres membres du groupe. Tout sujet se trouvait dans cette situation et donc dans un groupe existaient autant de séries de prix que de sujets. Nous avons montré que, par la mise en place de ces interdépendances croisées, les comportements stratégiques sont réduits. De plus, la cohérence des décisions est rétablie. Les sujets commencent par prévoir le prix en se basant uniquement sur les prévisions passées et sur l'évolution du prix réel et, avec le temps, ils coordonnent leur prévision avec leur propre production. Ceci témoigne de la sophistication de leur raisonnement.

En résumé, nous avons apporté des éclaircissements sur la manière de laquelle les agents prennent leurs décisions en situation de feedback négatif et mettent un place un raisonnement sophistiqué. Nous avons montré pourquoi un raisonnement sophistiqué de type éductif a plus de chances d'aboutir à des situations stables telles les environnements de feedback négatif. Nous avons montré que cela ne tient pas uniquement à la capacité cognitive des agents, mais aussi aux facteurs stabilisants de l'environnement. Ainsi les agents assimilent mieux l'information et transforment plus rapidement leurs croyances réflectives en croyances intuitives. Les résultats de leurs interactions sont plus stables. Cependant, nous sommes conscients du fait que notre analyse ne prend pas en compte tous les éléments qui pourraient apparaître lors d'une prise de décision. Nous avons délibérément choisi de tester le raisonnement éductif dans des situations stables et simples. De plus, le travail expérimental sur les mesures des croyances est d'emblée biaisé par le fait que le temps notionnel, qui passe dans la tête des gens, n'est pas observable directement. Au contraire, l'issue de tout processus de raisonnement est parfaitement mesurable par la méthode expérimentale. Nous avons observé les processus de convergence des nombres gagnants et des séries des prix et leur stabilité. Nous avons intégré dans notre thèse des éléments de la recherche en psychologie. Cependant, des situations plus compliquées devraient être testées, et plus d'expériences devraient être conduites dans la lignée du travail de psychologie expérimentale.

Nos expériences contribuent donc à la littérature en économie expérimentale par l'introduction des jeux du concours de beauté à feedback négatif et par la prise en compte du raisonnement éductif dans les marchés de type cobweb à information complète. Nous avons montré que les caractéristiques en termes de feedback de l'environnement avaient un impact sur les décisions des agents. Nous avons montré que la rationalité peut être volontairement limitée dès lors que l'on peut passer des croyances réflectives aux croyances intuitives.

Au début de cette thèse, nous sommes partis du constat que les jeux classiques du concours de beauté n'avaient jamais été appliquées dans leur forme la plus simple aux situations de feedback négatif et que peu de travaux expérimentaux adressaient directement la question du raisonnement éductif. En plus, dans la réalité, il semblait que les environnements à feedback négatif étaient plus stables que les situations de feedback positif. Maintenant, nous nous posons plusieurs questions :

Premièrement, dans la réalité, les environnements ont des dimensions multiples dans lesquelles le feedback positif et négatif coexistent. Quelle serait la validité de nos résultats dans de telles situations?

Deuxièmement, les individus sont souvent impliqués dans des problèmes de décisions plus complexes que les jeux du concours de beauté ou les marchés linéaires à un bien. Obtiendrions-nous une profondeur de raisonnement équivalente dans de telles situations ou dans des situations instables?

Troisièmement, les décisions économiques et sociales et la transformation des croyances réflectives en croyances intuitives dépendent de points focaux psychologiques ou d'influences sociales. La mise en place de travaux en psychologie et économie expérimentale serait nécessaire afin de déterminer ces points et leur influence sur le raisonnement éductif. Aussi, les phénomènes de mimétisme devraient être pris en compte.

Finalement, ces quelques éléments que nous citons nous amènent à dire qu'un travail global devrait être entrepris afin de prendre en compte toute la complexité du raisonnement éductif.

# Appendices

# Apppendix Chapter 4

As an example, these are the instructions for $p=2/3$ (in French).

### Bienvenue

L'expérience à laquelle vous allez participer est destinée à l'étude de la prise de décision. Si vous suivez les instructions et que vous prenez les bonnes décisions, vous pouvez gagner une somme d'argent non-négligeable. Toutes vos réponses seront traitées de façon anonyme et seront recueillies au travers d'un réseau informatique. Vous indiquerez vos choix à l'ordinateur devant lequel vous êtes assis et celui-ci vous communiquera les informations sur le déroulement du jeu et sur l'évolution des gains.

La somme totale d'argent gagnée pendant l'expérience vous sera versée, en liquide, à la fin de celle-ci.

Lorsque tous les participants auront pris connaissance des instructions, une description générale sera effectuée à voix haute.

### Cadre général de l'expérience

L'expérience comporte 10 périodes. 16 personnes participent à cette expérience, y compris vous-même. Les 16 personnes sont réparties en deux groupes indépendants de 8 personnes chacun. Ces deux groupes resteront les mêmes tout au long des 10 périodes. Vous avez été affecté par tirage au sort à l'un des deux groupes. Vous ne connaissez pas l'identité des 7 autres personnes de votre groupe, et les autres membres de votre groupe ne connaissent pas votre identité.

**A chaque période vous devez prendre une décision : choisir un nombre.**

A chacune des 10 périodes de l'expérience, vous pouvez réaliser un gain. Votre gain à chaque période dépendra de vos décisions et des décisions des autres membres de votre groupe.

La façon de calculer les gains sera explicitée dans la suite des instructions.

A la fin de l'expérience, la somme totale d'argent gagnée vous sera remise en liquide.

### Le choix d'un nombre

Au début de chaque période, vous devez choisir un nombre. Au même moment, chaque membre de votre groupe doit également choisir un nombre. Lorsque vous choissez votre nombre, vous ne connaissez pas les choix des autres membres de votre groupe et les autres membres de votre groupe ne connaissent pas votre choix au moment de prendre leur décision.

Le nombre que vous devez choisir doit être compris entre 0 et 100. Tous les membres de votre groupe doivent choisir des nombres compris entre 0 et 100. Si vous voulez que votre choix vous amène à réaliser des gains, vous devez suivre la règle qui permet d'attribuer les gains aux gagnants de chaque période.

**Comment est déterminé le gagnant de chaque période**

A chaque période, un gagnant sera déterminé. Ce gagnant sera déterminé de la façon suivante:

Le gagnant de chaque période sera la personne qui choisira le nombre le plus proche d'une cible qui est déterminée de la façon suivante:

$$\textbf{la cible = 100 - } \frac{2}{3} \times \textbf{(la moyenne de tous les nombres choisis dans le groupe, y compris vous-même)}$$

*Exemple :*

Si les 7 autres membres de votre groupe choisissent chacun 0 et vous même vous choisissez 8, alors la valeur de la cible est :

$$100 - \frac{2}{3} \times \left(\frac{7 \times 0 + 8}{8}\right) = 99{,}33$$

Dans ce cas, vous êtes le gagnant parce que votre choix (8) est plus proche de 99,33 que les choix des autres (0).

**Détermination des gains**

Le gagnant de chaque période reçoit 8 euros. Si à une période il y a plusieurs gagnants, les 8 euros sont divisé entre eux. Par exemple, si à une période 4 personnes ont toutes été également proches de la cible, il y a 4 gagnants, et chacun recevra 2 euros. Seul les gagnants se verront attribuer des euros. Les autres participants (qui n'ont pas gagné) ne recevront rien.

A la fin de chaque période l'ordinateur vous communiquera la cible, déterminée selon la règle ci-dessus, si vous avez gagné, et le montant de votre gain pour la période en cours et depuis le début du jeu.

Toutes les périodes se déroulent de la même manière.

**Synthèse**

A chaque période vous, ainsi que les 7 autres membres de votre groupe, devez choisir un nombre, compris entre 0 et 100. Vos choix sont transmis à travers le réseau informatique. La moyenne de tous les nombres choisis dans votre groupe sera calculée, multipliée par 2/3 et le résultat retranché de 100. Le nombre obtenu est **la cible**. Si vous désirez gagner des points dans une période, vous devez essayer d'être le plus proche possible de cette cible. Celui qui dans une période a été le plus proche de la cible est le gagnant de cette période. Il reçoit 8 euros. S'il y a plusieurs gagnants, les 8 euros sont divisés entre eux de manière égale. Ainsi, pour les 10 périodes, une personne ayant gagné seule à chaque période pourrait recevoir 80 euros.

A chaque fin de période, l'ordinateur vous indiquera quelle a été la cible pour la période courante, si vous avez gagné (1 = oui, 0 = non), et le montant de votre gain pour cette période. Toutes ces informations seront stockés dans un tableau qui sera affiché à l'écran pendant toute la durée de l'expérience. Il vous rappellera pour toutes les périodes passées vos choix, les nombres gagnants, si vous avez gagné, vos gains période par période et vos gains totaux.

Avant de commencer le jeu, nous allons procéder à une lecture à voix haute des instructions. Par la suite, un questionnaire vérifiera votre bonne compréhension des règles du jeu.

Bonne chance!

# Appendix Chapter 6

- **Instructions:** As an example, these are the instructions for the *large slow* market (in French).

**Bienvenue**

L'expérience à laquelle vous allez participer est destinée à l'étude de la prise de décision. Si vous suivez les instructions et que vous prenez les bonnes décisions, vous pouvez gagner une somme d'argent non-négligeable. Toutes vos réponses seront traitées de façon anonyme et seront recueillies au travers d'un réseau informatique. Vous indiquerez vos choix à l'ordinateur devant lequel vous êtes assis et celui-ci vous communiquera les informations sur le déroulement du jeu et sur l'évolution des gains.

La somme totale d'argent gagnée pendant l'expérience vous sera versée, en liquide, à la fin de celle-ci.

Lorsque tous les participants auront pris connaissance des instructions, une description générale sera effectuée à voix haute.

**Cadre général de l'expérience**

L'expérience comporte 40 périodes. 20 personnes participent à cette expérience y compris vous-même. Les 20 personnes sont réparties en deux groupes indépendants de 10 personnes chacun. Ces deux groupes resteront les mêmes tout au long des 40 périodes. Vous avez été affecté par tirage au sort à l'un des deux groupes. Vous ne connaissez pas l'identité des 9 autres personnes de votre groupe, et les autres membres de votre groupe ne connaissent pas votre identité.

Au début de l'expérience, vous disposerez d'un capital de 50 000 points. A chacune des 40 périodes de l'expérience, vous allez soit réaliser un gain, soit subir une perte. Les points gagnés seront ajoutés à votre capital de départ et les points perdus y seront retranchés.

**A chaque période vous serez amené à prendre deux décisions** :
-une décision de production
-une prévision de prix
**Votre gain ou perte** de chaque période sera composé de deux éléments :
-un gain ou une perte résultant de votre décision de production
-un gain ou une perte résultant de votre prévision

Votre perte ou votre gain à chaque période dépendra de vos décisions et des décisions des autres membres de votre groupe. Plus précisément, le gain ou la perte issu(e) de votre décision de production dépendra non seulement de votre propre décision de production, mais aussi des décisions de production des autres membres de votre groupe. Par contre, le gain ou la perte lié(e) à votre décision de production ne sera pas affecté(e) par votre prévision de prix. En revanche, le gain ou la perte de votre prévision de prix dépendra de l'ensemble des décisions de production.

La façon de calculer les gains et les pertes sera explicitée dans la suite des instructions.

A la fin de l'expérience, vos points disponibles (pertes déduites et gains rajoutés) seront convertis en Euros. La procédure de conversion sera détaillée à la fin des instructions.

**La décision de production**

Au début de chaque période, vous devez décider d'une quantité à produire. Au même moment, chaque membre de votre groupe doit décider également d'une quantité à produire. Les décisions de production des 10 joueurs du groupe forment la **quantité totale produite.** Cette quantité totale produite **sera vendue sur le marché**. Au moment de prendre votre décision de production, vous ne connaissez pas le prix de vente. De même, les autres membres de votre groupe ne connaîtront pas le prix de vente. Par contre, vous connaîtrez votre coût de production, qui est retracé dans le tableau 1. Ce tableau est le même pour tous les membres de votre groupe.

NB. L'expression « nup » signifie « nombre d'unités produites ».

Tableau 1 : **Coûts de production**

| *Numéro de l'intervalle* | *Intervalles de production* | *Coût de production de chaque unité supplémentaire produite* | *Coût de production de toutes les unités produites par vous-même* |
|---|---|---|---|
| 1 | de 1 à 4 | 20 | nup × 20 |
| 2 | de 5 à 8 | 25 | (nup - 4) × 25 + 80 |
| 3 | de 9 à 12 | 30 | (nup - 8) × 30 + 180 |
| 4 | de 13 à 16 | 35 | (nup - 12) × 35 + 300 |
| 5 | de 17 à 20 | 40 | (nup - 16) ×40 + 440 |
| 6 | de 21 à 24 | 45 | (nup - 20) ×45 + 600 |
| 7 | de 25 à 28 | 50 | (nup - 24) ×50 + 780 |
| 8 | de 29 à 32 | 55 | (nup - 28) × 55 + 980 |
| 9 | de 33 à 36 | 60 | (nup - 32) × 60 + 1200 |
| 10 | de 37 à 40 | 65 | (nup - 36) ×65 + 1440 |
| 11 | de 41 à 44 | 70 | (nup - 40) ×70 + 1700 |
| 12 | de 45 à 48 | 75 | (nup - 44) ×75 + 1980 |
| 13 | de 49 à 52 | 80 | (nup - 48) ×80 + 2280 |
| 14 | de 53 à 56 | 85 | (nup - 52) ×85 + 2600 |
| 15 | de 57 à 60 | 90 | (nup - 56) ×90 + 2940 |
| 16 | de 61 à 64 | 95 | (nup - 60) ×95 + 3300 |
| 17 | de 65 à 68 | 100 | (nup - 64) ×100 + 3680 |
| 18 | de 69 à 72 | 105 | (nup - 68) ×105 + 4080 |
| 19 | de 73 à 76 | 110 | (nup - 72) ×110 + 4500 |
| 20 | de 77 à 80 | 115 | (nup - 76) ×115 + 4840 |
| 21 | de 81 à 84 | 120 | (nup - 80) ×120 + 5400 |
| 22 | de 85 à 88 | 125 | (nup - 84) ×125 + 5880 |
| 23 | de 89 à 92 | 130 | (nup - 88) ×130 + 6380 |
| 24 | de 93 à 96 | 135 | (nup - 92) ×135 + 6900 |
| 25 | de 96 à 100 | 140 | (nup - 96) ×140 + 7440 |
| 26 | de 100 à plus | 145 | (nup - 100) ×145 + 8000 |

La première colonne du tableau 1 indique le numéro de l'intervalle de production dans lequel vous vous situez. Ces intervalles de production sont détaillés dans la deuxième colonne du tableau. Par exemple, si vous produisez 7 unités, vous vous situez dans l'intervalle 2.

Notez que le coût de production unitaire est différent pour chaque intervalle. Ceci est indiqué dans la troisième colonne. Ainsi chacune des 4 premières unités (intervalle 1) vous coûte 20 points ; chacune des unités de 5 à 8 (intervalle 2) vous coûte 25 points ; chacune des unités de 9 à 12 (intervalle 3) vous coûte 30 points etc.…

La dernière colonne du tableau retrace les règles de calcul de vos coûts de production totaux pour chaque intervalle de production.

La lecture de ce tableau est simple. Nous allons l'illustrer à l'aide de trois exemples.

*Exemple 1 :*

Supposons que vous décidiez de produire nup = 3. Vous vous situez alors dans l'intervalle de production numéro 1 (entre 1 et 4 unités). Chacune de vos 3 unités produites vous coûte alors 20 points. Votre coût total de production pour les 3 unités est alors égal à $3 \times 20 = 60$ points.

*Exemple 2 :*

Supposons que vous décidiez de produire nup = 5. Les 4 premières unités produites correspondent à l'intervalle de production numéro 1 et la 5$^{ème}$ unité correspond à l'intervalle de production numéro 2. Les 4 premières unités vous coûtent donc 20 points chacune et la 5$^{ème}$ unité vous coûte 25 points. Votre coût total de production pour ces 5 unités est donc de $(4 \times 20) + (1 \times 25) = 80 + 25 = 105$ points.

*Exemple 3 :*

Supposons que vous décidiez de produire nup = 18. Pour connaître le coût total de votre production, vous devez faire le calcul suivant : les 4 premières unités vous coûtent chacune 20 points, soit $4 \times 20 = 80$ points. Les 4 unités suivantes (de la 5$^{ème}$ à la 8$^{ème}$ incluses) vous coûtent chacune 25 points, soit $4 \times 25 = 100$ points. Les 4 unités suivantes (de 9 à 12 incluses) coûtent chacune 30 points, soit $4 \times 30 = 120$ points. Les 4 unités suivantes (de 13 à 16 incluses) coûtent chacune 35 points, soit $4 \times 35 = 140$ points. Finalement les 2 dernières unités coûtent chacune 40 points, donc $2 \times 40 = 80$ points. Au total, vos 18 unités vous coûtent $80 + 100 + 120 + 140 + 80 = 520$ points au total.

Vous n'avez pas besoin de faire tous ces calculs, car la dernière colonne du tableau vous indique les formules permettant d'obtenir le coût total directement. Il suffit de remplacer *nup* par la quantité que vous voulez produire dans l'intervalle correspondant. Par exemple, si vous voulez produire 18 unités comme dans l'exemple précédent, votre coût total sera calculé en vous reportant à l'intervalle numéro 5 et en remplaçant dans la formule *nup* par 18 soit $(18 - 16) \times 40 + 440 = 520$.

**Fixation du prix de vente**

A chaque période, le prix de vente auquel vous pouvez écouler votre production dépendra de votre propre décision de production et des décisions de production des autres membres de votre groupe pour cette période (c'est-à-dire de la **production totale de votre groupe**). Le prix dépend de la quantité totale produite selon une grille de prix qui a été fixée par les acheteurs et qui est décrite dans le tableau numéro 2.

Tableau 2 : **Grille de prix en fonction de la production totale**

| *Numéro de l'intervalle* | *Intervalles de quantités* | *Prix proposé pour une unité de cet intervalle* |
|---|---|---|
| 1 | de 1 à 44 | 100 |
| 2 | de 45 à 89 | 95 |
| 3 | de 90 à 134 | 90 |
| 4 | de 135 à 179 | 85 |
| 5 | de 180 à 224 | 80 |
| 6 | de 225 à 269 | 75 |
| 7 | de 270 à 314 | 70 |
| 8 | de 315 à 359 | 65 |
| 9 | de 360 à 404 | 60 |
| 10 | de 405 à 449 | 55 |
| 11 | de 450 à 494 | 50 |
| 12 | de 495 à 539 | 45 |
| 13 | de 540 à 584 | 40 |
| 14 | de 585 à 629 | 35 |
| 15 | de 630 à 674 | 30 |
| 16 | de 675 à 719 | 25 |
| 17 | de 720 à 764 | 20 |
| 18 | de 765 à 809 | 15 |
| 19 | de 810 à 854 | 10 |
| 20 | de 855 à 899 | 5 |
| 21 | de 900 à plus | 0 |

La première colonne de ce tableau précise chacun des intervalles de production totale. La deuxième colonne retrace les intervalles de production totale disponible. La dernière colonne indique le prix unitaire auquel chaque unité sera vendue. **Toutes les unités produites seront vendues au même prix.**

Par exemple, si la production totale de votre groupe est de 486 unités, chaque unité sera vendue au prix de 50 points l'unité. Ce prix est le même pour chacune des 486 unités. Si, par exemple, votre part dans la production totale est de 37 unités, votre recette sera égale à $37 \times 50 = 1850$ points. Le prix de 50 points s'appliquera bien sur à tous les membres de votre groupe. Pour connaître votre gain ou votre perte il faudra retrancher le coût de production de cette recette.

**Le gain ou la perte de votre décision de production**

Le profit de votre production est calculé selon la règle suivante :

**Votre profit pour la période en cours = votre quantité produite × prix pour cette période – votre coût total de production**.

Prenons quelques exemples pour illustrer cette règle.

*Exemple 1 :*

Supposons que vous décidiez de produire nup = 33 unités et que les autres membres de votre groupe produisent ensemble 292 unités, alors la production totale est de 33 + 292 = 325 unités. Pour cette quantité, le prix de vente est de 65 points par unité. Votre recette est donc égale à $33 \times 65 = 2145$ points.

Votre coût total de production est calculé en appliquant les formules du tableau 1 (intervalle numéro 7) : $(33 - 32) \times 60 + 1200 = 1260$ points.

**Votre profit** pour cette période est donc de 2145 - 1260 = 885 points. Ce profit s'ajoute à votre capital disponible en début de période.

*Exemple 2 :*

Supposons que vous décidiez de produire nup = 33 unités et que les autres membres de votre groupe produisent ensemble 620 unités, alors la production totale sera de 33 + 620 = 653 unités. Pour cette quantité, le prix de vente est de 30 points par unité. Votre recette est donc de $33 \times 30 = 990$ points.

Votre coût total de production est de : $(33 - 32) \times 60 + 1200 = 1260$ points.

**Votre perte** pour cette période est donc de 990 -1260 = - 270 points. Cette perte sera retranchée à votre capital disponible en début de période.

*Exemple 3 :*

Supposons que vous décidiez de produire nup = 33 unités et que les autres membres de votre groupe produisent ensemble 820 unités, alors la production totale est de 33 + 800 = 853 unités. Pour cette quantité, le prix de vente est de 10 points par unité. Votre recette est donc égale à $33 \times 10 = 330$ points.

Calculons votre coût total de production : $(33 - 32) \times 60 + 1200 = 1260$ points.

**Votre perte** pour cette période est donc de 330 - 1260= - 930 points. Cette perte sera retranchée à votre capital disponible en début de période.

**Votre prévision et le gain ou la perte lié à cette prévision**

A chaque période, en plus de votre décision de production, vous devez faire une prévision du prix de vente de la production du groupe. Votre prévision vous fait gagner des points supplémentaires lorsqu'elle est « bonne » et perdre des points supplémentaires lorsqu'elle est « mauvaise ».

Si vous ne faites aucune erreur de prévision, c'est-à-dire si vous devinez exactement le prix de vente de la production, vous gagnerez 500 points. Si vous faites une erreur de prévision, des points seront déduits de cette somme. Le nombre de points déduits sera calculé en fonction de votre erreur selon la formule suivante :

$$\text{Gain ou perte de la prévision} = 500 - 0{,}8 \times (\text{prix prévu} - \text{prix établi sur le marché})^2$$

L'erreur se calcule donc en comparant votre prévision de prix au prix qui s'établit sur le marché. Plus votre prévision de prix est proche du prix effectivement réalisé sur le marché, plus vous gagnerez des points supplémentaires.

Comparons deux cas : dans le premier cas, vous prévoyez un prix de 90 points et le prix de vente est de 40 points. Votre perte liée à la prévision sera de : $500 - 0{,}8 \times (90 - 40)^2 = - 1500$.

Dans le deuxième cas, vous prévoyez un prix de 80 points et le prix qui s'établit sur le marché est de 100 points. Avec la règle de calcul précédente, votre gain dans le deuxième cas sera $500 - 0{,}8 \times (80 - 100)^2 = 180$ (les valeurs indiquées sont plus proches dans le deuxième cas).

**La règle de calcul de votre gain ou perte lié à la prévision est telle que vous avez toujours intérêt à annoncer votre vraie prévision.**

## Récapitulatif

L'expérience consiste en une succession de 40 périodes au cours desquelles vous devez choisir une quantité à produire et faire une prévision du prix qui s'établira à la fin de la période. Tous les membres de votre groupe disposent des mêmes informations que vous et devront prendre le même type de décisions. La quantité que vous décidez de produire, ainsi que les quantités produites par les 9 autres membres de votre groupe, seront vendues sur le marché au même prix de vente. Tous les membres de votre groupe choisissent les quantités à produire et font leur prévision de prix en même temps.

Au début de l'expérience vous disposez d'un capital de 50 000 points. A chaque période, des points peuvent s'ajouter à ce capital si vous réalisez des gains ou en être retranchés si vous subissez des pertes. A chaque période, le prix de vente sera calculé par l'ordinateur à partir des décisions de production de tous les membres de votre groupe. Ce prix vous sera alors communiqué en même temps que votre gain ou perte. Le capital restant (en poins) est reporté à la période suivante.

A chaque période donc vous devez prendre deux décisions :
-la quantité que vous voulez produire (un nombre entier compris entre 1 et 900)
-la prévision du prix de vente(un nombre compris entre 0 et 100, multiple de 5)

A chaque période, les informations suivantes vous seront communiquées :
-le prix de vente
-votre coût de production
-votre gain ou perte lié(e) à la production
-votre gain ou perte lié(e) à la prévision du prix
-votre capital restant pour la période suivante

Avant de démarrer l'expérience, vous prendrez part à deux périodes essai. **Lors de ces deux périodes essai, les décisions des quatre autres membres de votre groupe seront simulées par l'ordinateur.** Ces périodes essai ont uniquement pour but de vous familiariser avec l'environnement de l'expérience. Les points gagnés au cours de ces périodes essai ne seront pas comptabilisés.

A la première période essai, chacun des 9 autres membres simulés de votre groupe va choisir une quantité de 100 unités à produire (donc 900 unités au total produites par les 9 autres membres de votre groupe).

A la deuxième période essai, chacun des 9 autres membres simulés de votre groupe va choisir une quantité de 1 unités à produire (donc 9 unités au total produites par les 9 autres membres de votre groupe) .

Une fois les deux périodes essai terminées, l'ordinateur vous affectera à votre groupe pour les 40 périodes de l'expérience. Le jeu se déroulera avec les autres membres du groupe comme cela a été décrit dans ces instructions. A l'écran, un bouton « Historique » vous permettra d'accéder à l'ensemble des décisions des périodes précédentes.

A la fin des 40 périodes, votre capital final sera converti en euros selon la règle 5000 points = 1 euro. Ainsi, si votre capital final est par exemple de 100 000 points, vous recevrez

20 euros. Nous vous demandons de remplir alors la feuille de commentaires, et d’attendre à votre place jusqu’à ce qu’un moniteur vienne vous chercher.

Avant de démarrer l’expérience, un questionnaire vérifiera votre bonne compréhension des instructions.

N’hésitez pas à lever la main si vous avez une question !

**Bonne chance !**

- **Unit root tests:**

Critical values: 5%=-2.942 1%=-3.617; Constant included

**Fast small**

| | t-adf | beta Y_1 | \sigma | lag | t-DY_lag | t-prob | F-prob | AIC |
|---|---|---|---|---|---|---|---|---|
| gr1 | -4.8610** | -0.23968 | 3.3765 | 2 | 0.41048 | 0.6841 | | 2.5355 |
| gr1 | -5.7676** | -0.17846 | 3.3349 | 1 | 1.6917 | 0.0999 | 0.6841 | 2.4865 |
| gr1 | -5.9477** | 0.043284 | 3.4225 | 0 | | | 0.2423 | 2.5133 |
| gr2 | -3.2944* | -0.040427 | 3.7081 | 2 | -1.4258 | 0.1633 | | 2.7228 |
| gr2 | -5.3822** | -0.32794 | 3.7640 | 1 | 1.0161 | 0.3167 | 0.1633 | 2.7286 |
| gr2 | -6.9145** | -0.14156 | 3.7658 | 0 | | | 0.2276 | 2.7044 |
| gr3 | -2.8079 | 0.28628 | 2.4659 | 2 | -0.58294 | 0.5639 | | 1.9069 |
| gr3 | -3.8379** | 0.20263 | 2.4419 | 1 | -0.18700 | 0.8528 | 0.5639 | 1.8631 |
| gr3 | -5.4367** | 0.17647 | 2.4080 | 0 | | | 0.8303 | 1.8101 |
| gr4 | -4.0061** | -0.24625 | 11.251 | 2 | 0.56830 | 0.5737 | | 4.9427 |
| gr4 | -4.7412** | -0.13503 | 11.138 | 1 | 0.012885 | 0.9898 | 0.5737 | 4.8983 |
| gr4 | -6.9202** | -0.13281 | 10.978 | 0 | | | 0.8515 | 4.8443 |
| gr5 | -3.0288* | 0.31029 | 4.4114 | 2 | 0.35846 | 0.7223 | | 3.0702 |
| gr5 | -3.3116* | 0.35009 | 4.3545 | 1 | 0.064511 | 0.9489 | 0.7223 | 3.0200 |
| gr5 | -4.0705** | 0.35740 | 4.2921 | 0 | | | 0.9360 | 2.9661 |
| gr6 | -3.1603* | 0.022369 | 4.2686 | 2 | -1.2414 | 0.2232 | | 3.0044 |
| gr6 | -5.0003** | -0.21751 | 4.3024 | 1 | 0.37789 | 0.7079 | 0.2232 | 2.9960 |
| gr6 | -7.9347** | -0.14386 | 4.2494 | 0 | | | 0.4394 | 2.9461 |

**Slow small**

| | t-adf | beta Y_1 | \sigma | lag | t-DY_lag | t-prob | F-prob | AIC |
|---|---|---|---|---|---|---|---|---|
| Gr1 | -3.8257** | 0.39332 | 4.7002 | 2 | -0.85606 | 0.3981 | | 3.1970 |
| Gr1 | -4.0579** | 0.36921 | 4.6817 | 1 | -0.89605 | 0.3765 | 0.3981 | 3.1649 |
| Gr1 | -4.8189** | 0.31407 | 4.6685 | 0 | | | 0.4735 | 3.1342 |
| Gr2 | -4.8838** | -0.24435 | 3.9430 | 2 | 0.44815 | 0.6570 | | 2.8457 |
| Gr2 | -5.3776** | -0.18986 | 3.8964 | 1 | 0.87259 | 0.3890 | 0.6570 | 2.7977 |
| Gr2 | -6.5483** | -0.058548 | 3.8831 | 0 | | | 0.6278 | 2.7658 |
| Gr3 | -5.8756** | -0.49457 | 3.6615 | 2 | 2.9663 | 0.0056 | | 2.6976 |
| Gr3 | -4.6449** | -0.023904 | 4.0598 | 1 | 0.59227 | 0.5576 | 0.0056 | 2.8799 |
| Gr3 | -5.8740** | 0.065539 | 4.0220 | 0 | | | 0.0171 | 2.8361 |
| Gr4 | -1.4301 | 0.70496 | 2.2273 | 2 | -0.013230 | 0.9895 | | 1.7034 |
| Gr4 | -1.6408 | 0.70370 | 2.1943 | 1 | -2.9615 | 0.0055 | 0.9895 | 1.6493 |
| Gr4 | -3.9985** | 0.37288 | 2.4256 | 0 | | | 0.0227 | 1.8247 |
| Gr5 | -3.6080* | 0.35609 | 2.5089 | 2 | 0.16175 | 0.8725 | | 1.9415 |
| Gr5 | -3.7326** | 0.36310 | 2.4727 | 1 | -0.15135 | 0.8806 | 0.8725 | 1.8882 |
| Gr5 | -4.4234** | 0.35049 | 2.4380 | 0 | | | 0.9761 | 1.8349 |
| Gr6 | -5.0619** | -0.47885 | 9.0277 | 2 | 1.9300 | 0.0622 | | 4.5024 |
| Gr6 | -4.6963** | -0.14029 | 9.3825 | 1 | 0.74132 | 0.4636 | 0.0622 | 4.5553 |
| Gr6 | -5.9563** | -0.012584 | 9.3219 | 0 | | | 0.1314 | 4.5173 |

**Divergent with**

| | t-adf | beta Y_1 | \sigma | lag | t-DY_lag | t-prob | F-prob | AIC |
|---|---|---|---|---|---|---|---|---|
| gr1 | -3.3640* | 0.22139 | 3.6298 | 2 | -0.50073 | 0.6199 | | 2.6801 |
| gr1 | -4.1540** | 0.16578 | 3.5895 | 1 | -0.066786 | 0.9471 | 0.6199 | 2.6337 |
| gr1 | -5.1822** | 0.15812 | 3.5381 | 0 | | | 0.8807 | 2.5797 |
| gr2 | -3.6840** | -0.038554 | 6.7644 | 2 | 0.93398 | 0.3571 | | 3.9252 |
| gr2 | -3.7868** | 0.10389 | 6.7517 | 1 | -0.46238 | 0.6468 | 0.3571 | 3.8972 |
| gr2 | -5.8742** | 0.026644 | 6.6755 | 0 | | | 0.5863 | 3.8494 |
| gr3 | -2.6485 | 0.29171 | 11.366 | 2 | -0.45130 | 0.6547 | | 4.9631 |
| gr3 | -3.2348* | 0.23722 | 11.232 | 1 | -2.1190 | 0.0415 | 0.6547 | 4.9152 |
| gr3 | -6.7749** | -0.13131 | 11.779 | 0 | | | 0.1167 | 4.9852 |
| gr4 | -3.6975** | 0.23097 | 17.257 | 2 | 0.082959 | 0.9344 | | 5.7982 |
| gr4 | -4.6373** | 0.24136 | 17.003 | 1 | 2.4781 | 0.0183 | 0.9344 | 5.7444 |
| gr4 | -3.6606** | 0.45283 | 18.209 | 0 | | | 0.0644 | 5.8563 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| gr5 | -4.5668** | -0.27439 | 3.6574 | 2 | 1.2483 | 0.2207 | | 2.6953 |
| gr5 | -4.6557** | -0.075597 | 3.6873 | 1 | 1.0475 | 0.3022 | 0.2207 | 2.6874 |
| gr5 | -5.3971** | 0.090141 | 3.6924 | 0 | | | 0.2765 | 2.6651 |
| gr6 | -2.6271 | 0.32573 | 4.1579 | 2 | -0.99720 | 0.3259 | | 2.9518 |
| gr6 | -3.6612** | 0.19413 | 4.1575 | 1 | -0.12869 | 0.8984 | 0.3259 | 2.9274 |
| gr6 | -4.9524** | 0.17595 | 4.0987 | 0 | | | 0.6078 | 2.8739 |

**Fast large**

| | t-adf | beta Y_1 | \sigma | lag | t-DY_lag | t-prob | F-prob | AIC |
|---|---|---|---|---|---|---|---|---|
| gr1 | -2.6508 | 0.43110 | 2.4021 | 2 | -1.3835 | 0.1758 | | 1.8545 |
| gr1 | -2.7953 | 0.39628 | 2.4342 | 1 | -1.6018 | 0.1184 | 0.1758 | 1.8568 |
| gr1 | -5.0466** | 0.16667 | 2.4881 | 0 | | | 0.1187 | 1.8756 |
| gr2 | -3.1043* | 0.22715 | 6.7702 | 2 | 0.13117 | 0.8964 | | 3.9269 |
| gr2 | -3.6271** | 0.24440 | 6.6716 | 1 | 0.13784 | 0.8912 | 0.8964 | 3.8733 |
| gr2 | -4.5249** | 0.26185 | 6.5775 | 0 | | | 0.9823 | |

**Slow large**

| | t-adf | beta Y_1 | \sigma | lag | t-DY_lag | t-prob | F-prob | AIC |
|---|---|---|---|---|---|---|---|---|
| gr1 | -2.5346 | 0.64911 | 2.7568 | 2 | -1.4664 | 0.1520 | | 2.1299 |
| gr1 | -2.5398 | 0.64267 | 2.8030 | 1 | -1.8607 | 0.0715 | 0.1520 | 2.1390 |
| gr1 | -3.4991* | 0.53541 | 2.8999 | 0 | | | 0.0712 | 2.1819 |
| gr2 | -3.1384* | 0.46190 | 6.6383 | 2 | -0.68293 | 0.4994 | | 3.8875 |
| gr2 | -4.1428** | 0.40038 | 6.5860 | 1 | -0.21107 | 0.8341 | 0.4994 | 3.8475 |
| gr2 | -5.2552** | 0.38300 | 6.4955 | 0 | | | 0.7763 | 3.7947 |

**Divergent large**

| | t-adf | beta Y_1 | \sigma | lag | t-DY_lag | t-prob | F-prob | AIC |
|---|---|---|---|---|---|---|---|---|
| gr1 | -2.2241 | 0.60550 | 5.0554 | 2 | 0.50070 | 0.6199 | | 3.3427 |
| gr1 | -2.2015 | 0.61719 | 4.9994 | 1 | -1.1384 | 0.2629 | 0.6199 | 3.2962 |
| gr1 | -3.2432* | 0.51499 | 5.0205 | 0 | | | 0.4761 | 3.2796 |
| gr2 | -4.2404** | -0.36964 | 8.9277 | 2 | 0.82376 | 0.4160 | | 4.4801 |
| gr2 | -4.8524** | -0.19956 | 8.8854 | 1 | 0.77960 | 0.4410 | 0.4160 | 4.4464 |
| gr2 | -6.2935** | -0.059069 | 8.8354 | 0 | | | 0.5336 | 4.4101 |

# Appendix Chapter 7

- **Instructions:** As an example, these are the instructions for the *divergent without* market (in French).

**Bienvenue**

L'expérience à laquelle vous allez participer est destinée à l'étude de la prise de décision. Si vous suivez les instructions et que vous prenez les bonnes décisions, vous pouvez gagner une somme d'argent non-négligeable. Toutes vos réponses seront traitées de façon anonyme et seront recueillies au travers d'un réseau informatique. Vous indiquerez vos choix à l'ordinateur devant lequel vous êtes assis et celui-ci vous communiquera les informations sur le déroulement du jeu et sur l'évolution des gains.

La somme totale d'argent gagnée pendant l'expérience vous sera versée, en liquide, à la fin de celle-ci.

Lorsque tous les participants auront pris connaissance des instructions, une description générale sera effectuée à voix haute.

**Cadre général de l'expérience**

L'expérience comporte 40 périodes. 15 personnes participent à cette expérience y compris vous-même. Les 15 personnes sont réparties en trois groupes indépendants de 5 personnes chacun. Ces trois groupes resteront les mêmes tout au long des 40 périodes. Vous avez été affecté par tirage au sort à l'un des trois groupes. Vous ne connaissez pas l'identité des 4 autres personnes de votre groupe, et les autres membres de votre groupe ne connaissent pas votre identité.

Au début de l'expérience, vous disposerez d'un capital de 100 000 points. A chacune des 40 périodes de l'expérience, vous allez soit réaliser un gain soit subir une perte. Les points gagnés seront ajoutés à votre capital de départ et les points perdus y seront retranchés.

**A chaque période vous serez amené à prendre une décision de production.**

Votre gain ou perte de chaque période sera déterminé(e) par votre décision de production.

Votre gain ou votre perte à chaque période dépendra de vos décisions et des décisions des autres membres de votre groupe. Plus précisément, le gain ou la perte issu(e) de votre décision de production dépendra non seulement de votre propre décision de production, mais aussi des décisions de production des autres membres de votre groupe.

La façon de calculer les gains et les pertes sera explicitée dans la suite des instructions.

A la fin de l'expérience, les points qui resteront à votre disposition (pertes déduites et gains rajoutés) seront convertis en Euros. La procédure de conversion sera détaillée à la fin des instructions.

## La décision de production

Au début de chaque période, vous devez décider d'une quantité à produire. Au même moment, chaque membre de votre groupe doit décider également d'une quantité à produire. Les décisions de production des 5 joueurs du groupe forment la **quantité totale produite.** Cette quantité totale produite **sera vendue sur le marché**. Au moment de prendre votre décision de production, vous ne connaissez pas le prix de vente. De même, les autres membres de votre groupe ne connaîtront pas le prix de vente. Par contre, vous connaîtrez votre coût de production, qui est retracé dans le tableau 1. Ce tableau est le même pour tous les membres de votre groupe.

NB. L'expression « nup » signifie « nombre d'unités produites ».

Tableau 1 : **Coûts de production**

| *Numéro de l'intervalle* | *Intervalles de production* | *Coût de production de chaque unité supplémentaire produite* | *Coût total de production* |
|---|---|---|---|
| 1 | de 1 à 9 | 45 | nup ×45 |
| 2 | de 10 à 30 | 50 | (nup - 9) ×50 + 405 |
| 3 | de 31 à 51 | 55 | (nup - 30) × 55 + 1455 |
| 4 | de 52 à 72 | 60 | (nup - 51) × 60 + 2610 |
| 5 | de 73 à 93 | 65 | (nup - 72) ×65 + 3870 |
| 6 | de 94 à 114 | 70 | (nup - 93) ×70 + 5235 |
| 7 | de 115 à 135 | 75 | (nup - 114) ×75 + 6705 |
| 8 | de 136 à 156 | 80 | (nup - 135) ×80 + 8280 |
| 9 | de 157 à 177 | 85 | (nup - 156) ×85 + 9960 |
| 10 | de 178 à 198 | 90 | (nup - 177) ×90 + 11745 |
| 11 | de 199 à 219 | 95 | (nup - 198) ×95 + 13635 |
| 12 | de 220 à 240 | 100 | (nup - 219) ×100 + 15630 |
| 13 | de 241 à 261 | 105 | (nup - 240) ×105 + 17730 |
| 14 | de 262 à 282 | 110 | (nup - 261) ×110 + 19935 |
| 15 | de 283 à 303 | 115 | (nup - 282) ×115 + 22245 |
| 16 | de 304 à plus | 120 | (nup - 303) ×120 + 24660 |

La première colonne du tableau 1 indique le numéro de l'intervalle de production dans lequel vous vous situez. Par exemple, si vous produisez 20 unités, vous vous situez dans l'intervalle 2. Ces intervalles de production sont détaillés dans la deuxième colonne du tableau.

Notez que le coût de production unitaire est différent pour chaque intervalle. Ainsi chacune des 9 premières unités (intervalle 1) vous coûte 45 points ; chacune des unités de 10 à 30 (intervalle 2) vous coûte 50 points ; chacune des unités de 31 à 51 (intervalle 3) vous coûte 55 points etc.…

La dernière colonne du tableau retrace les règles de calcul de vos coûts de production totaux pour chaque intervalle de production.

La lecture de ce tableau est simple. Nous allons l'illustrer à l'aide de trois exemples.

*Exemple 1 :*

Supposons que vous décidiez de produire nup = 5. Vous vous situez alors dans l'intervalle de production numéro 1 (entre 1 et 9 unités). Chacune de vos 5 unités produites vous coûte alors 45 points. Votre coût total de production pour les 5 unités est alors égal à $5 \times 45 = 225$ points.

*Exemple 2 :*

Supposons que vous décidiez de produire nup = 10. Les 9 premières unités produites correspondent à l'intervalle de production numéro 1 et la 10$^{\text{ème}}$ unité correspond à l'intervalle de production numéro 2. Les 9 premières unités vous coûtent donc 45 points chacune et la 10$^{\text{ème}}$ unité vous coûte 50 points. Votre coût total de production pour ces 10 unités est donc de $(9 \times 45) + (1 \times 50) = 405 + 50 = 455$ points.

*Exemple 3 :*

Supposons que vous décidiez de produire nup = 36. Pour connaître le coût total de votre production, vous devez faire le calcul suivant : les 9 premières unités vous coûtent chacune 45 points, soit $9 \times 45 = 405$ points au total. Les 21 unités suivantes (de la 10ième à la 30$^{\text{ième}}$, incluses) vous coûtent chacune 50 points, soit $21 \times 50 = 1050$ points au total. Les 30 premières unités coûtent donc $405 + 1050 = 1455$ points. Les 6 unités suivantes (de 31 à 36, incluses) coûtent chacune 55 points, soit $6 \times 55 = 330$ points au total. Donc les 36 unités coûtent $(405 + 1050) + 330 = 1785$ points au total.

Vous n'avez pas besoin de faire tout ces calculs, car la dernière colonne du tableau vous indique les formules permettant d'obtenir le coût total directement. Il suffit de remplacer *nup* par la quantité que vous voulez produire dans l'intervalle correspondant. Par exemple, si vous voulez produire 36 unités comme dans l'exemple précédent, votre coût total sera calculé en vous reportant à l'intervalle numéro 4 et en remplaçant dans la formule *nup* par 36, soit $(36 - 30) \times 55 + 1455 = 1785$.

## Fixation du prix de vente

A chaque période, le prix de vente auquel vous pouvez écouler votre production dépendra de votre propre décision de production et des décisions de production des autres membres de votre groupe pour cette période (c'est-à-dire de la **production totale de votre groupe**). Le prix de vente dépend de la quantité totale produite selon une grille fixée par les acheteurs, décrite dans le tableau numéro 2.

Tableau 2 : **Grille de prix de vente en fonction de la production totale**

| *Numéro de l'intervalle* | *Intervalles de quantités* | *Prix de vente* |
|---|---|---|
| 1 | de 1 à 44 | 100 |
| 2 | De 45 à 89 | 95 |
| 3 | de 90 à 134 | 90 |
| 4 | de 135 à 179 | 85 |
| 5 | de 180 à 224 | 80 |
| 6 | de 225 à 269 | 75 |
| 7 | de 270 à 314 | 70 |
| 8 | de 315 à 359 | 65 |
| 9 | de 360 à 404 | 60 |
| 10 | de 405 à 449 | 55 |
| 11 | de 450 à 494 | 50 |
| 12 | de 495 à 539 | 45 |
| 13 | de 540 à 584 | 40 |
| 14 | de 585 à 629 | 35 |
| 15 | de 630 à 674 | 30 |
| 16 | de 675 à 719 | 25 |
| 17 | de 720 à 764 | 20 |
| 18 | de 765 à 809 | 15 |
| 19 | de 810 à 854 | 10 |
| 20 | de 855 à 899 | 5 |
| 21 | de 900 à plus | 0 |

La première colonne de ce tableau précise chacun des intervalles de production totale. La deuxième détaille ces intervalles. La dernière colonne indique le prix unitaire auquel chaque unité sera vendue. **Toutes les unités produites seront vendues au même prix.**

Par exemple, si la production totale de votre groupe est de 486 unités, chaque unité sera vendue au prix de 50 points l'unité. Ce prix est le même pour chacune des 486 unités. Si, par exemple, votre part dans la production totale est de 97 unités, votre recette sera égale à $97 \times 50 = 4850$ points. Le prix de 50 points par unité s'appliquera bien sûr à tous les membres de votre groupe. Pour connaître votre gain ou votre perte il faudra retrancher le coût de production à cette recette.

**Le gain ou la perte de votre décision de production**

Le profit de votre production est calculé selon la règle suivante :

**Votre profit pour la période en cours = votre quantité produite × prix de vente – votre coût total de production.**

Prenons quelques exemples pour illustrer cette règle.

*Exemple 1 :*

Supposons que vous décidiez de produire 53 unités et que les autres membres de votre groupe produisent ensemble 272 unités, alors la production totale est de $53 + 272 = 325$

unités. Pour cette quantité, le prix de vente est de 65 points par unité. Votre recette est donc égale à $53 \times 65 = 3445$ points.

Votre coût total de production est calculé en appliquant les formules du tableau 1 (intervalle numéro 4) : $(53 - 51) \times 60 + 2610 = 2730$ points.

**Votre profit** pour cette période est donc de $3445 - 2730 = 715$ points. Ce profit s'ajoute dans cet exemple à votre capital disponible en début de période.

*Exemple 2 :*

Supposons que vous décidiez de produire 53 unités et que les autres membres de votre groupe produisent ensemble 600 unités, alors la production totale sera de $53 + 600 = 653$ unités. Pour cette quantité, le prix de vente est de 30 points par unité. Votre recette est donc égale à $53 \times 30 = 1590$ points.

Votre coût total de production est de : $(53 - 51) \times 60 + 2610 = 2730$ points.

**Votre perte** pour cette période est donc de $1590 - 2730 = -1140$ points. Cette perte sera retranchée à votre capital disponible en début de période.

*Exemple 3 :*

Supposons que vous décidiez de produire 53 unités et que les autres membres de votre groupe produisent ensemble 800 unités, alors la production totale est de $53 + 800 = 853$ unités. Pour cette quantité, le prix de vente est de 10 points par unité. Votre recette est donc égale à $53 \times 10 = 530$ points.

Calculons votre coût total de production : $(53 - 51) \times 60 + 2610 = 2730$ points.

**Votre perte** pour cette période est donc de $530 – 2730 = -2200$ points. Cette perte sera retranchée à votre capital disponible en début de période.

## Récapitulatif

L'expérience consiste en une succession de 40 périodes au cours desquelles vous devez choisir une quantité à produire. Tous les membres de votre groupe disposent des mêmes informations que vous et devront prendre la même décision. La quantité que vous décidez de produire, ainsi que les quantités produites par les 4 autres membres de votre groupe, seront vendues au même prix de vente. Tous les membres de votre groupe choisissent les quantités à produire en même temps.

Au début de l'expérience vous disposez d'un capital de 100 000 points. A chaque période, des points peuvent s'ajouter à ce capital si vous réalisez des gains ou en être retranchés si vous subissez des pertes. A chaque période, le prix de vente sera calculé par l'ordinateur à partir des décisions de production de tous les membres de votre groupe. Ce prix vous sera alors communiqué en même temps que votre gain ou perte. Le capital restant (en points) est reporté à la période suivante.

A chaque période vous devez donc prendre donc une décision : la quantité que vous voulez produire (un nombre entier compris entre 0 et 900)

A chaque période, les informations suivantes vous seront communiquées :
- le prix de vente
- votre coût de production

- votre gain ou perte lié(e) à la production
- votre capital restant pour la période suivante

Avant de démarrer l'expérience, vous prendrez part à deux périodes essai. **Lors de ces deux périodes essai, les décisions des quatre autres membres de votre groupe seront simulées par l'ordinateur.** Ces périodes essai ont uniquement pour but de vous familiariser avec l'environnement de l'expérience. Les points gagnés au cours de ces périodes essai ne seront pas comptabilisés.

A la première période essai, chacun des 4 autres membres simulés de votre groupe va choisir une quantité de 225 unités à produire (donc 900 unités au total produites par les quatre autres membres de votre groupe).

A la deuxième période essai, chacun des 4 autres membres simulés de votre groupe va choisir une quantité de 2 unités à produire (donc 8 unités au total produites par les quatre autres membres de votre groupe) .

Une fois les deux périodes essai terminées, l'ordinateur vous affectera à votre groupe pour les 40 périodes de l'expérience. Le jeu se déroulera avec les autres membres du groupe comme cela a été décrit dans ces instructions. A l'écran, un bouton « Historique » vous permettra d'accéder à l'ensemble des décisions des périodes précédentes.

A la fin des 40 périodes, votre capital final sera converti en euros selon la règle 10 000 points = 1 euro. Ainsi, si votre capital final est par exemple de 200 000 points, vous recevrez 20 euros. Nous vous demandons de remplir alors la feuille de commentaires, et d'attendre à votre place jusqu'à ce qu'un moniteur vienne vous chercher.

Avant de démarrer l'expérience, un questionnaire vérifiera votre bonne compréhension des instructions.

N'hésitez pas à lever la main si vous avez une question !

**Bonne chance !**

- **Unit root tests:**

The ADF test consists in running a regression of the first difference of the series against the series lagged once, lagged difference terms, and optionally, a constant and a time trend.

$$\Delta X_t = \alpha + \gamma X_{t-1} + \beta_1 \Delta X_{t-1} + \ldots + \beta_h \Delta X_{t-h} + u_t$$

Test stands for ($\gamma$-1) = 0. A large negative t-statistic rejects the hypothesis of a unit root and suggests that the series is stationary.

**Fast without**

Critical values: 5%=-2.942 1%=-3.617; Constant included

| | t-adf | beta Y_1 | \sigma | lag | t-DY_lag | t-prob | F-prob | AIC |
|---|---|---|---|---|---|---|---|---|
| Gr1 | -2.5529 | 0.46975 | 2.9022 | 2 | -1.2184 | 0.2317 | | 2.2327 |
| Gr1 | -2.9754* | 0.40100 | 2.9228 | 1 | -1.9088 | 0.0648 | 0.2317 | 2.2227 |
| Gr1 | -4.9860** | 0.16939 | 3.0312 | 0 | | | 0.0902 | 2.2704 |
| Gr2 | -3.5254* | 0.20160 | 2.7610 | 2 | -0.68336 | 0.4992 | | 2.1330 |
| Gr2 | -4.4145** | 0.12787 | 2.7393 | 1 | 1.0348 | 0.3081 | 0.4992 | 2.0930 |
| Gr2 | -4.6297** | 0.24279 | 2.7421 | 0 | | | 0.4755 | 2.0700 |
| Gr3 | -3.1124* | 0.59153 | 1.6123 | 2 | -1.0282 | 0.3113 | | 1.0571 |
| Gr3 | -3.4222* | 0.56164 | 1.6136 | 1 | -0.29239 | 0.7718 | 0.3113 | 1.0346 |
| Gr3 | -3.7456** | 0.55000 | 1.5924 | 0 | | | 0.5702 | 0.98301 |

**Fast with**

Critical values: 5%=-2.942 1%=-3.617; Constant included

| | t-adf | beta Y_1 | \sigma | lag | t-DY_lag | t-prob | F-prob | AIC |
|---|---|---|---|---|---|---|---|---|
| gr1 | -4.8610** | -0.23968 | 3.3765 | 2 | 0.41048 | 0.6841 | | 2.5355 |
| gr1 | -5.7676** | -0.17846 | 3.3349 | 1 | 1.6917 | 0.0999 | 0.6841 | 2.4865 |
| gr1 | -5.9477** | 0.043284 | 3.4225 | 0 | | | 0.2423 | 2.5133 |
| gr2 | -3.2944* | -0.040427 | 3.7081 | 2 | -1.4258 | 0.1633 | | 2.7228 |
| gr2 | -5.3822** | -0.32794 | 3.7640 | 1 | 1.0161 | 0.3167 | 0.1633 | 2.7286 |
| gr2 | -6.9145** | -0.14156 | 3.7658 | 0 | | | 0.2276 | 2.7044 |
| gr3 | -2.8079 | 0.28628 | 2.4659 | 2 | -0.58294 | 0.5639 | | 1.9069 |
| gr3 | -3.8379** | 0.20263 | 2.4419 | 1 | -0.18700 | 0.8528 | 0.5639 | 1.8631 |
| gr3 | -5.4367** | 0.17647 | 2.4080 | 0 | | | 0.8303 | 1.8101 |
| gr4 | -4.0061** | -0.24625 | 11.251 | 2 | 0.56830 | 0.5737 | | 4.9427 |
| gr4 | -4.7412** | -0.13503 | 11.138 | 1 | 0.012885 | 0.9898 | 0.5737 | 4.8983 |
| gr4 | -6.9202** | -0.13281 | 10.978 | 0 | | | 0.8515 | 4.8443 |
| gr5 | -3.0288* | 0.31029 | 4.4114 | 2 | 0.35846 | 0.7223 | | 3.0702 |
| gr5 | -3.3116* | 0.35009 | 4.3545 | 1 | 0.064511 | 0.9489 | 0.7223 | 3.0200 |
| gr5 | -4.0705** | 0.35740 | 4.2921 | 0 | | | 0.9360 | 2.9661 |
| gr6 | -3.1603* | 0.022369 | 4.2686 | 2 | -1.2414 | 0.2232 | | 3.0044 |
| gr6 | -5.0003** | -0.21751 | 4.3024 | 1 | 0.37789 | 0.7079 | 0.2232 | 2.9960 |
| gr6 | -7.9347** | -0.14386 | 4.2494 | 0 | | | 0.4394 | 2.9461 |

**Slow with**

Critical values: 5%=-2.942 1%=-3.617; Constant included

| | t-adf | beta Y_1 | \sigma | lag | t-DY_lag | t-prob | F-prob | AIC |
|---|---|---|---|---|---|---|---|---|
| Gr1 | -3.8257** | 0.39332 | 4.7002 | 2 | -0.85606 | 0.3981 | | 3.1970 |
| Gr1 | -4.0579** | 0.36921 | 4.6817 | 1 | -0.89605 | 0.3765 | 0.3981 | 3.1649 |
| Gr1 | -4.8189** | 0.31407 | 4.6685 | 0 | | | 0.4735 | 3.1342 |
| Gr2 | -4.8838** | -0.24435 | 3.9430 | 2 | 0.44815 | 0.6570 | | 2.8457 |
| Gr2 | -5.3776** | -0.18986 | 3.8964 | 1 | 0.87259 | 0.3890 | 0.6570 | 2.7977 |
| Gr2 | -6.5483** | -0.058548 | 3.8831 | 0 | | | 0.6278 | 2.7658 |
| Gr3 | -5.8756** | -0.49457 | 3.6615 | 2 | 2.9663 | 0.0056 | | 2.6976 |
| Gr3 | -4.6449** | -0.023904 | 4.0598 | 1 | 0.59227 | 0.5576 | 0.0056 | 2.8799 |
| Gr3 | -5.8740** | 0.065539 | 4.0220 | 0 | | | 0.0171 | 2.8361 |
| Gr4 | -1.4301 | 0.70496 | 2.2273 | 2 | -0.013230 | 0.9895 | | 1.7034 |
| Gr4 | -1.6408 | 0.70370 | 2.1943 | 1 | -2.9615 | 0.0055 | 0.9895 | 1.6493 |
| Gr4 | -3.9985** | 0.37288 | 2.4256 | 0 | | | 0.0227 | 1.8247 |
| Gr5 | -3.6080* | 0.35609 | 2.5089 | 2 | 0.16175 | 0.8725 | | 1.9415 |
| Gr5 | -3.7326** | 0.36310 | 2.4727 | 1 | -0.15135 | 0.8806 | 0.8725 | 1.8882 |
| Gr5 | -4.4234** | 0.35049 | 2.4380 | 0 | | | 0.9761 | 1.8349 |
| Gr6 | -5.0619** | -0.47885 | 9.0277 | 2 | 1.9300 | 0.0622 | | 4.5024 |
| Gr6 | -4.6963** | -0.14029 | 9.3825 | 1 | 0.74132 | 0.4636 | 0.0622 | 4.5553 |
| Gr6 | -5.9563** | -0.012584 | 9.3219 | 0 | | | 0.1314 | 4.5173 |

**Slow without**

Critical values: 5%=-2.942 1%=-3.617; Constant included

| | t-adf | beta Y_1 | \sigma | lag | t-DY_lag | t-prob | F-prob | AIC |
|---|---|---|---|---|---|---|---|---|
| Gr1 | -2.4061 | 0.60127 | 3.3449 | 2 | -1.8417 | 0.0745 | | 2.5166 |
| Gr1 | -2.7771 | 0.53518 | 3.4605 | 1 | -2.3708 | 0.0236 | 0.0745 | 2.5604 |
| Gr1 | -4.2932** | 0.33729 | 3.6819 | 0 | | | 0.0159 | 2.6594 |
| Gr2 | -3.6843** | -0.060092 | 6.0833 | 2 | -1.9204 | 0.0635 | | 3.7129 |
| Gr2 | -6.0849** | -0.40936 | 6.3192 | 1 | 1.9682 | 0.0572 | 0.0635 | 3.7648 |
| Gr2 | -6.4319** | -0.083407 | 6.5735 | 0 | | | 0.0294 | 3.8186 |
| Gr3 | -2.8827 | 0.48581 | 2.5630 | 2 | -0.55079 | 0.5855 | | 1.9842 |
| Gr3 | -3.1509* | 0.46132 | 2.5366 | 1 | -0.035935 | 0.9715 | 0.5855 | 1.9393 |
| Gr3 | -3.6046* | 0.45854 | 2.5002 | 0 | | | 0.8593 | 1.8853 |

**Divergent without**

Critical values: 5%=-2.942 1%=-3.617; Constant included

| | t-adf | beta Y_1 | \sigma | lag | t-DY_lag | t-prob | F-prob | AIC |
|---|---|---|---|---|---|---|---|---|
| gr1 | -1.9754 | 0.77839 | 4.0396 | 2 | -1.1932 | 0.2413 | | 2.8941 |
| gr1 | -2.1675 | 0.75815 | 4.0647 | 1 | -1.9555 | 0.0588 | 0.2413 | 2.8823 |
| gr1 | -3.2031* | 0.66445 | 4.2255 | 0 | | | 0.0858 | 2.9348 |
| gr2 | -4.9261** | 0.48024 | 3.1274 | 2 | -3.7051 | 0.0008 | | 2.3822 |
| gr2 | -4.3647** | 0.46078 | 3.6663 | 1 | -2.0711 | 0.0460 | 0.0008 | 2.6760 |
| gr2 | -5.3729** | 0.36086 | 3.8347 | 0 | | | 0.0005 | 2.7407 |
| gr3 | -3.6139* | 0.29907 | 4.3836 | 2 | 0.37409 | 0.7107 | | 3.0576 |
| gr3 | -3.7034** | 0.31948 | 4.3278 | 1 | 0.21052 | 0.8345 | 0.7107 | 3.0077 |
| gr3 | -4.2988** | 0.34003 | 4.2683 | 0 | | | 0.9127 | 2.9550 |

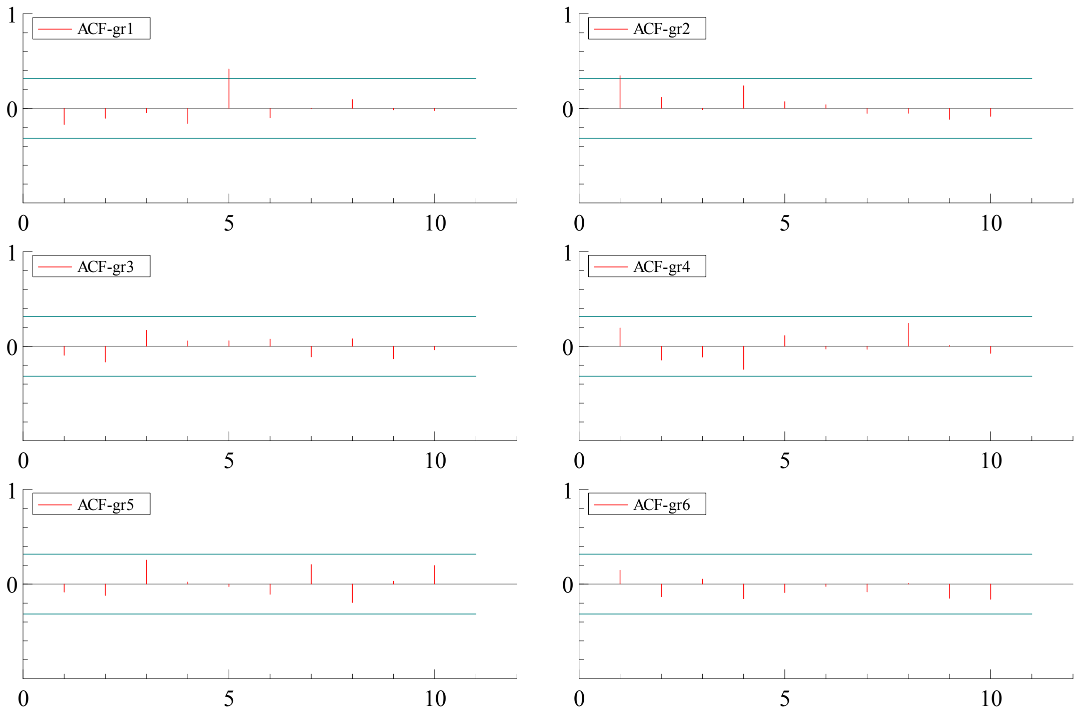
**Divergent with**

Critical values: 5%=-2.942 1%=-3.617; Constant included

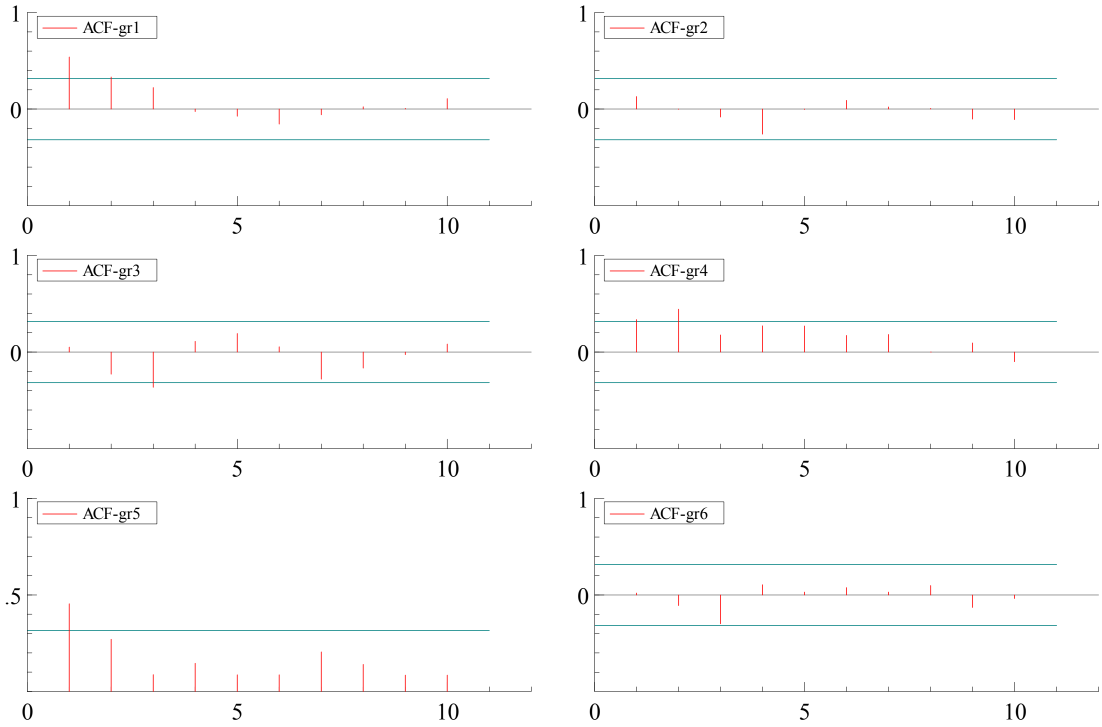
| | t-adf | beta Y_1 | \sigma | lag | t-DY_lag | t-prob | F-prob | AIC |
|---|---|---|---|---|---|---|---|---|
| gr1 | -3.3640* | 0.22139 | 3.6298 | 2 | -0.50073 | 0.6199 | | 2.6801 |
| gr1 | -4.1540** | 0.16578 | 3.5895 | 1 | -0.066786 | 0.9471 | 0.6199 | 2.6337 |
| gr1 | -5.1822** | 0.15812 | 3.5381 | 0 | | | 0.8807 | 2.5797 |
| gr2 | -3.6840** | -0.038554 | 6.7644 | 2 | 0.93398 | 0.3571 | | 3.9252 |
| gr2 | -3.7868** | 0.10389 | 6.7517 | 1 | -0.46238 | 0.6468 | 0.3571 | 3.8972 |
| gr2 | -5.8742** | 0.026644 | 6.6755 | 0 | | | 0.5863 | 3.8494 |
| gr3 | -2.6485 | 0.29171 | 11.366 | 2 | -0.45130 | 0.6547 | | 4.9631 |
| gr3 | -3.2348* | 0.23722 | 11.232 | 1 | -2.1190 | 0.0415 | 0.6547 | 4.9152 |
| gr3 | -6.7749** | -0.13131 | 11.779 | 0 | | | 0.1167 | 4.9852 |
| gr4 | -3.6975** | 0.23097 | 17.257 | 2 | 0.082959 | 0.9344 | | 5.7982 |
| gr4 | -4.6373** | 0.24136 | 17.003 | 1 | 2.4781 | 0.0183 | 0.9344 | 5.7444 |
| gr4 | -3.6606** | 0.45283 | 18.209 | 0 | | | 0.0644 | 5.8563 |
| gr5 | -4.5668** | -0.27439 | 3.6574 | 2 | 1.2483 | 0.2207 | | 2.6953 |
| gr5 | -4.6557** | -0.075597 | 3.6873 | 1 | 1.0475 | 0.3022 | 0.2207 | 2.6874 |
| gr5 | -5.3971** | 0.090141 | 3.6924 | 0 | | | 0.2765 | 2.6651 |
| gr6 | -2.6271 | 0.32573 | 4.1579 | 2 | -0.99720 | 0.3259 | | 2.9518 |
| gr6 | -3.6612** | 0.19413 | 4.1575 | 1 | -0.12869 | 0.8984 | 0.3259 | 2.9274 |
| gr6 | -4.9524** | 0.17595 | 4.0987 | 0 | | | 0.6078 | 2.8739 |

- ## Autocorrelations plots:

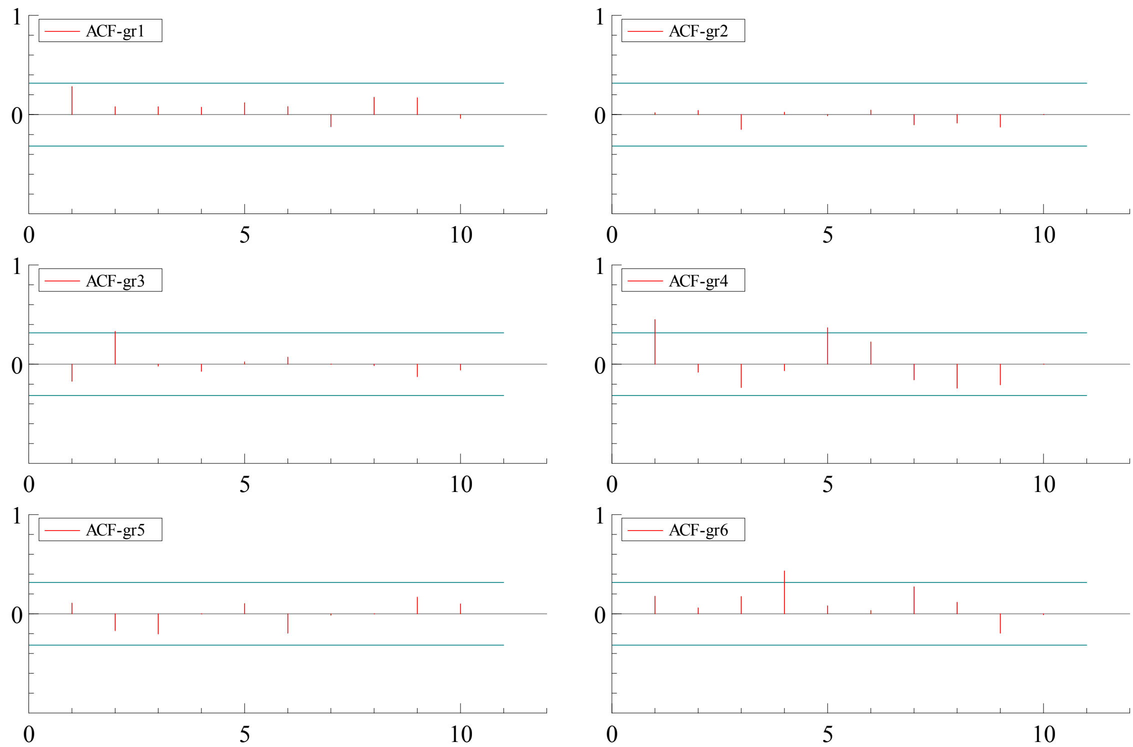
Autocorrelations plots for *fast with* groups:



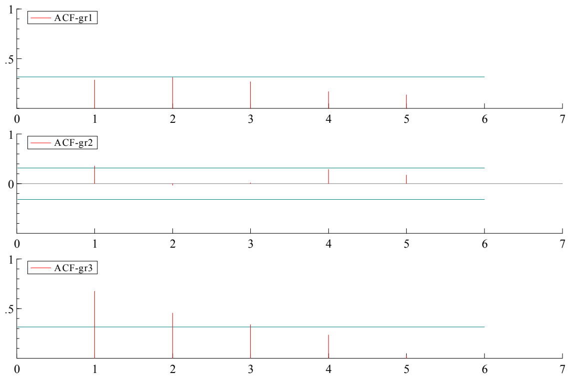
Autocorrelations plots for *slow with* groups:



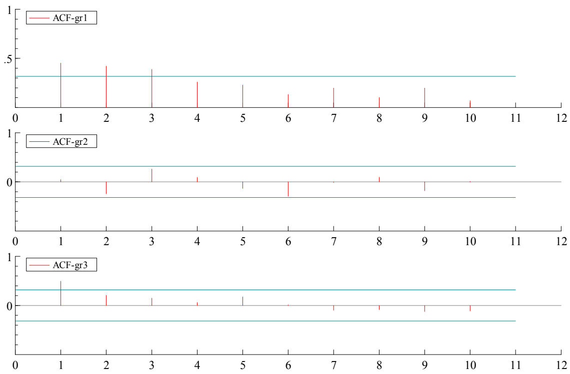

Autocorrelations plots for *divergent with* groups:



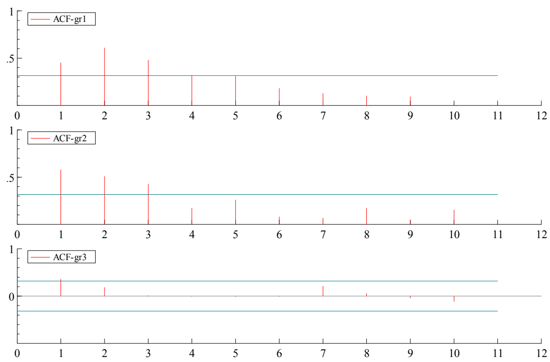
Autocorrelations plots for *fast without* groups:




Autocorrelations plots for *slow without* groups:

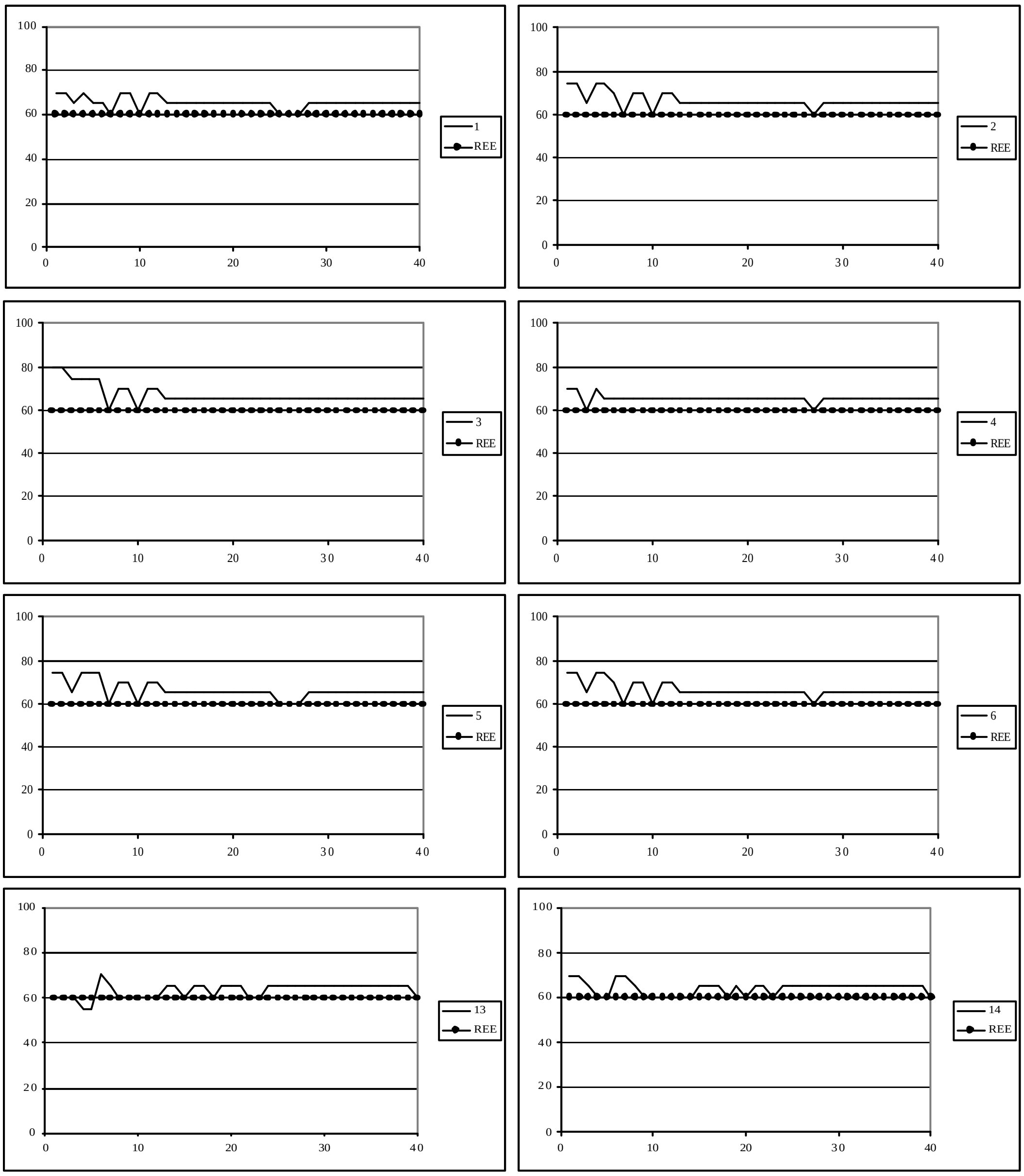


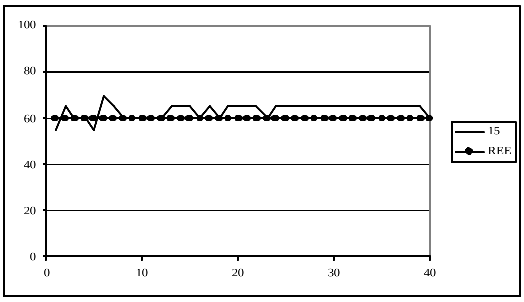

Autocorrelations plots for *divergence without* groups:



# Appendix Chapter 8

- **Price evolution in 12 *fast*, 12 *slow* and 12 *divergent* markets:**

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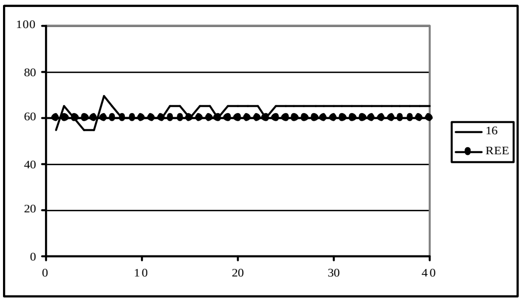
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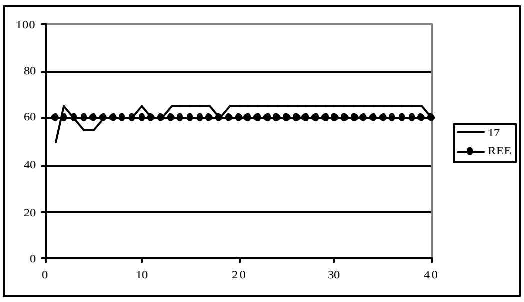
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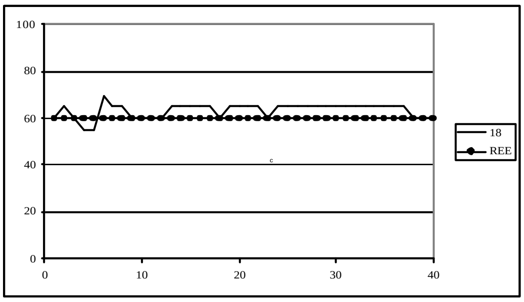
REE


18
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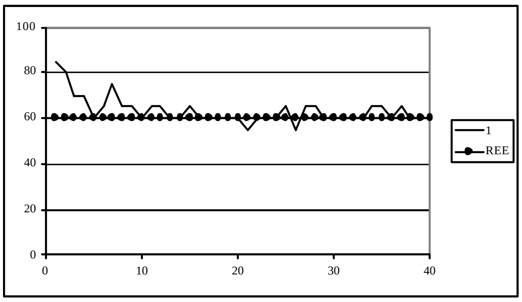
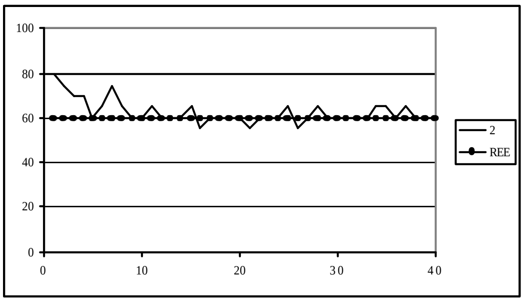

1
REE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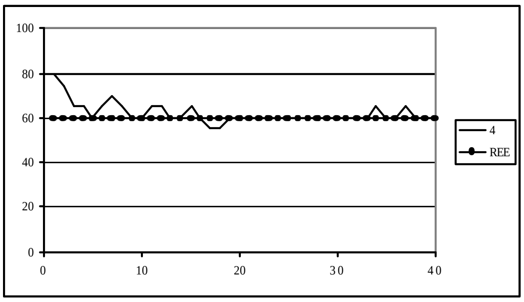
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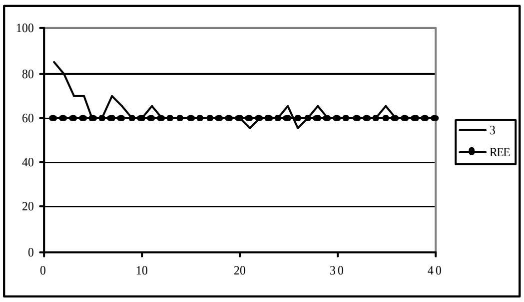
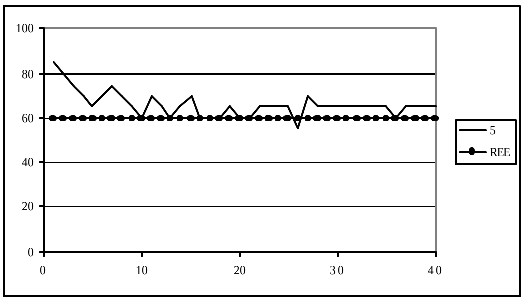
REE


3
REE


5
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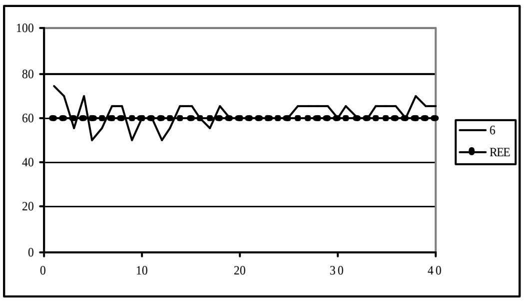
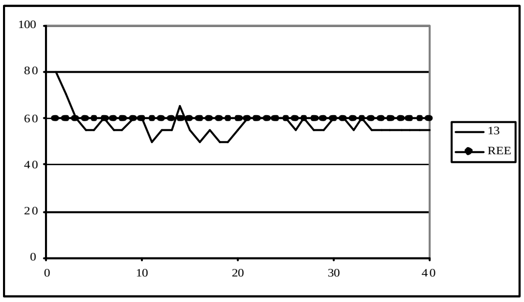

6
REE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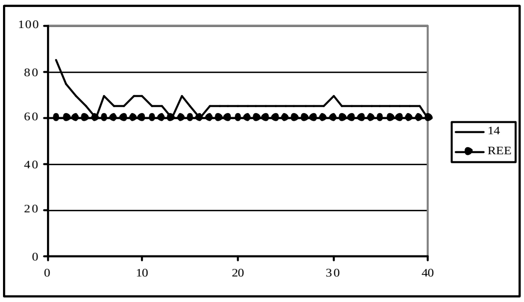
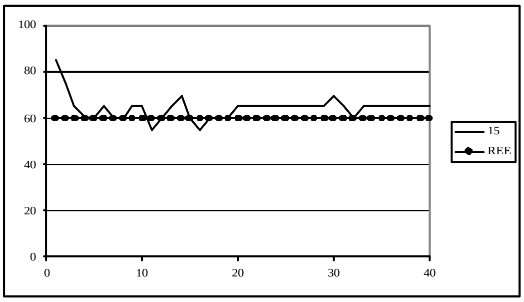
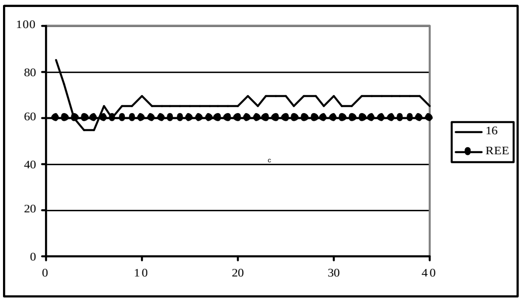
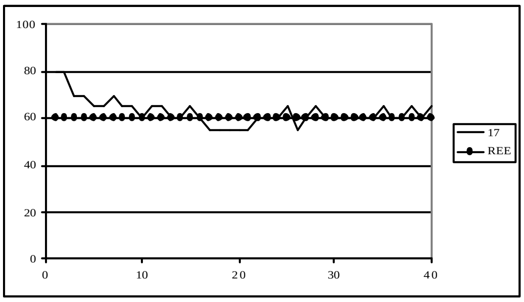
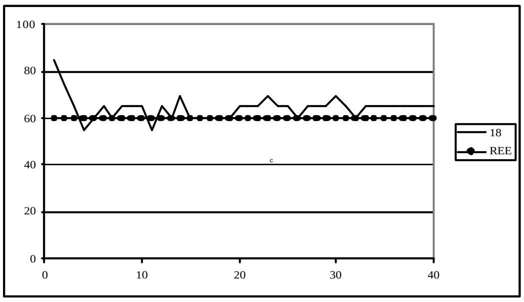
0 10 20 30 40
13
REE


0 20 40 60 80 100
0 10 20 30 40
14
REE


0 20 40 60 80 100
0 10 20 30 40
15
REE


0 20 40 60 80 100
0 10 20 30 40
16
REE


0 20 40 60 80 100
0 10 20 30 40
17
REE


0 20 40 60 80 100
0 10 20 30 40
18
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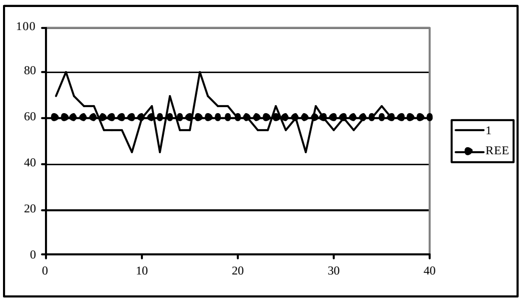
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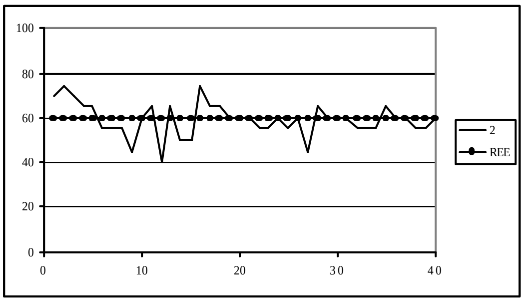
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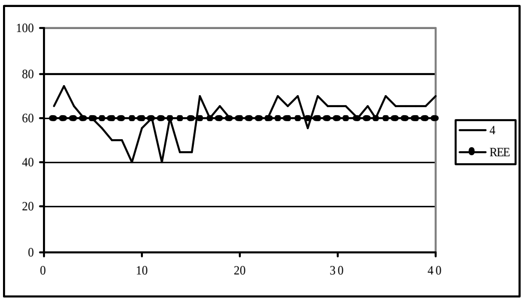
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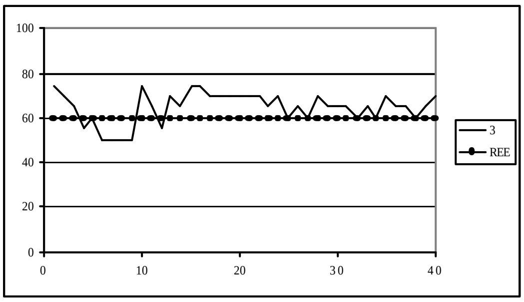
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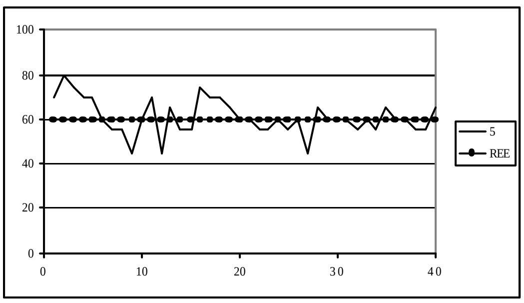
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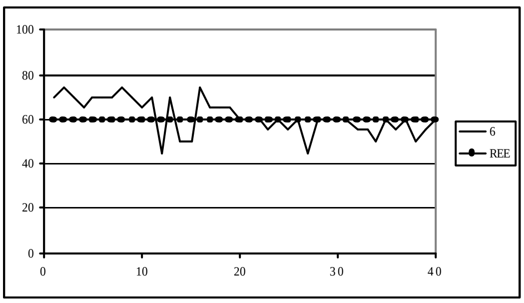
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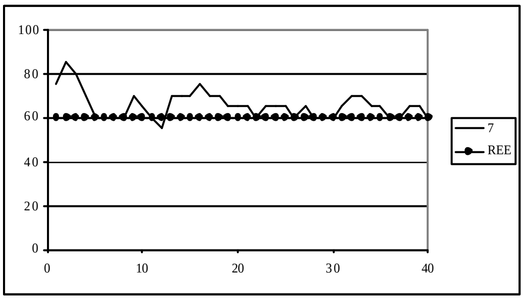
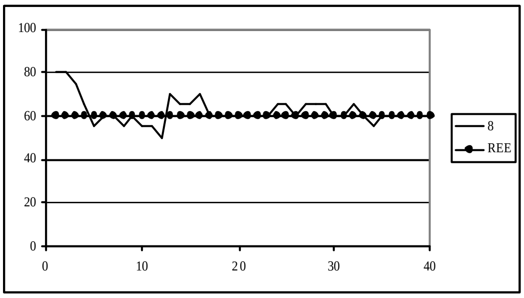
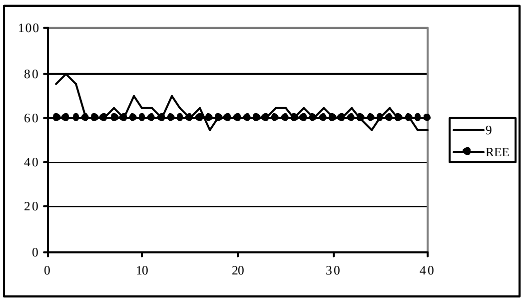
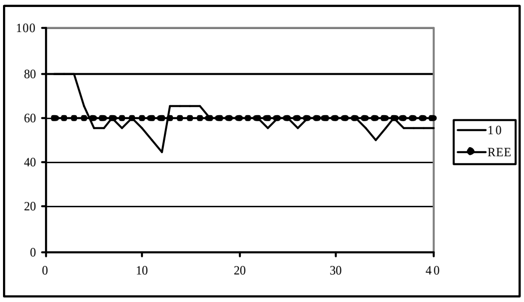
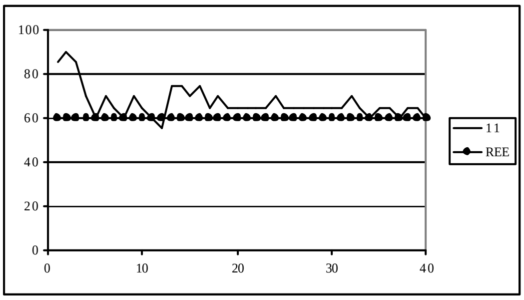
6
REE

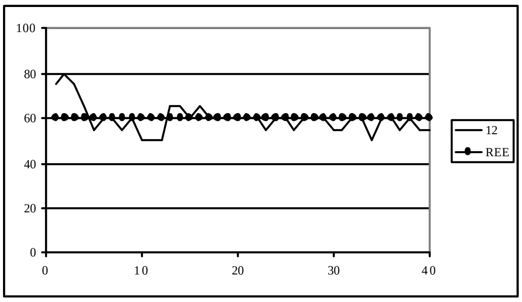



- **Variance decomposition for 18 *fast*, 18 *slow* and 18 *divergent* forecasts:**

***Fast treatment***

Variance Decomposition of PREV1:

| Period | S.E. | PRIX1 | PREV1 | PROD1 |
|---|---|---|---|---|
| 1 | 3.040069 | 3.747051 | 96.25295 | 0.000000 |
| 2 | 3.925839 | 37.44968 | 62.20447 | 0.345853 |
| 3 | 4.034416 | 40.59914 | 58.91966 | 0.481192 |
| 4 | 4.039118 | 40.64474 | 58.81593 | 0.539325 |
| 5 | 4.040337 | 40.63007 | 58.79814 | 0.571787 |
| 6 | 4.041226 | 40.62642 | 58.77821 | 0.595372 |
| 7 | 4.041785 | 40.62135 | 58.76478 | 0.613871 |
| 8 | 4.042180 | 40.61641 | 58.75524 | 0.628348 |
| 9 | 4.042480 | 40.61237 | 58.74806 | 0.639563 |
| 10 | 4.042711 | 40.60924 | 58.74255 | 0.648211 |

Variance Decomposition of PREV2:

| Period | S.E. | PRIX2 | PREV2 | PROD2 |
|---|---|---|---|---|
| 1 | 4.734146 | 13.07147 | 86.92853 | 0.000000 |
| 2 | 5.390991 | 10.49901 | 89.48989 | 0.011101 |
| 3 | 5.537520 | 9.956027 | 90.03272 | 0.011252 |
| 4 | 5.566654 | 9.852225 | 90.13546 | 0.012318 |
| 5 | 5.571999 | 9.833510 | 90.15381 | 0.012680 |
| 6 | 5.572938 | 9.830243 | 90.15700 | 0.012761 |
| 7 | 5.573100 | 9.829682 | 90.15754 | 0.012776 |
| 8 | 5.573128 | 9.829586 | 90.15763 | 0.012779 |
| 9 | 5.573132 | 9.829570 | 90.15765 | 0.012779 |
| 10 | 5.573133 | 9.829567 | 90.15765 | 0.012779 |

Variance Decomposition of PREV3:

| Period | S.E. | PRIX3 | PREV3 | PROD3 |
|---|---|---|---|---|
| 1 | 1.534542 | 2.183700 | 97.81630 | 0.000000 |
| 2 | 1.911310 | 4.859012 | 95.11799 | 0.022999 |
| 3 | 2.144870 | 9.374597 | 90.41848 | 0.206923 |
| 4 | 2.300684 | 13.49675 | 86.00721 | 0.496041 |
| 5 | 2.404274 | 16.57963 | 82.65179 | 0.768578 |
| 6 | 2.471692 | 18.70526 | 80.31417 | 0.980566 |
| 7 | 2.514588 | 20.10677 | 78.76215 | 1.131085 |
| 8 | 2.541341 | 21.00417 | 77.76351 | 1.232323 |
| 9 | 2.557746 | 21.56639 | 77.13564 | 1.297969 |
| 10 | 2.567665 | 21.91255 | 76.74805 | 1.339407 |

Variance Decomposition of PREV7:

| Period | S.E. | PRIX7 | PREV7 | PROD7 |
|---|---|---|---|---|
| 1 | 1.748100 | 0.261123 | 99.73888 | 0.000000 |
| 2 | 2.240213 | 38.22054 | 60.82679 | 0.952671 |
| 3 | 2.259797 | 37.64545 | 59.99373 | 2.360820 |
| 4 | 2.261192 | 37.70689 | 59.92837 | 2.364746 |
| 5 | 2.261391 | 37.71089 | 59.91886 | 2.370243 |
| 6 | 2.261397 | 37.71094 | 59.91868 | 2.370383 |
| 7 | 2.261398 | 37.71099 | 59.91860 | 2.370412 |
| 8 | 2.261398 | 37.71099 | 59.91859 | 2.370415 |
| 9 | 2.261398 | 37.71099 | 59.91859 | 2.370415 |
| 10 | 2.261398 | 37.71099 | 59.91859 | 2.370415 |

Variance Decomposition of PREV4:

| Period | S.E. | PRIX4 | PREV4 | PROD4 |
|---|---|---|---|---|
| 1 | 0.949845 | 3.844506 | 96.15549 | 0.000000 |
| 2 | 1.252298 | 34.19592 | 56.06628 | 9.737798 |
| 3 | 1.299832 | 31.86172 | 52.99783 | 15.14045 |
| 4 | 1.304272 | 32.19575 | 52.66101 | 15.14325 |
| 5 | 1.305118 | 32.15449 | 52.61266 | 15.23285 |
| 6 | 1.305198 | 32.16102 | 52.60690 | 15.23208 |
| 7 | 1.305214 | 32.16024 | 52.60604 | 15.23372 |
| 8 | 1.305216 | 32.16037 | 52.60594 | 15.23369 |
| 9 | 1.305216 | 32.16035 | 52.60593 | 15.23372 |
| 10 | 1.305216 | 32.16035 | 52.60592 | 15.23372 |

Variance Decomposition of PREV8:

| Period | S.E. | PRIX8 | PREV8 | PROD8 |
|---|---|---|---|---|
| 1 | 1.859589 | 0.448092 | 99.55191 | 0.000000 |
| 2 | 2.122597 | 3.299713 | 96.40091 | 0.299381 |
| 3 | 2.200327 | 3.408742 | 96.21046 | 0.380802 |
| 4 | 2.225747 | 3.495101 | 96.09927 | 0.405627 |
| 5 | 2.234120 | 3.516286 | 96.07007 | 0.413646 |
| 6 | 2.236902 | 3.524040 | 96.05967 | 0.416289 |
| 7 | 2.237827 | 3.526520 | 96.05631 | 0.417165 |
| 8 | 2.238135 | 3.527356 | 96.05519 | 0.417457 |
| 9 | 2.238238 | 3.527632 | 96.05481 | 0.417554 |
| 10 | 2.238272 | 3.527724 | 96.05469 | 0.417586 |

Variance Decomposition of PREV5:

| Period | S.E. | PRIX5 | PREV5 | PROD5 |
|---|---|---|---|---|
| 1 | 2.375714 | 17.58317 | 82.41683 | 0.000000 |
| 2 | 2.576670 | 19.83437 | 78.47306 | 1.692570 |
| 3 | 2.727838 | 25.76800 | 70.32141 | 3.910591 |
| 4 | 2.837000 | 29.42471 | 65.10605 | 5.469239 |
| 5 | 2.903219 | 31.19252 | 62.46258 | 6.344897 |
| 6 | 2.938710 | 31.96985 | 61.24508 | 6.785071 |
| 7 | 2.956059 | 32.29102 | 60.71881 | 6.990161 |
| 8 | 2.963938 | 32.41649 | 60.50366 | 7.079855 |
| 9 | 2.967298 | 32.46279 | 60.42032 | 7.116888 |
| 10 | 2.968653 | 32.47888 | 60.38976 | 7.131369 |

Variance Decomposition of PREV9:

| Period | S.E. | PRIX9 | PREV9 | PROD9 |
|---|---|---|---|---|
| 1 | 1.656470 | 0.012332 | 99.98767 | 0.000000 |
| 2 | 3.777642 | 80.14337 | 19.56396 | 0.292672 |
| 3 | 3.803464 | 79.09122 | 19.32305 | 1.585734 |
| 4 | 3.803631 | 79.08568 | 19.32142 | 1.592891 |
| 5 | 3.803632 | 79.08569 | 19.32142 | 1.592891 |
| 6 | 3.803632 | 79.08569 | 19.32142 | 1.592891 |
| 7 | 3.803632 | 79.08569 | 19.32142 | 1.592891 |
| 8 | 3.803632 | 79.08569 | 19.32142 | 1.592891 |
| 9 | 3.803632 | 79.08569 | 19.32142 | 1.592891 |
| 10 | 3.803632 | 79.08569 | 19.32142 | 1.592891 |

Variance Decomposition of PREV6:

| Period | S.E. | PRIX6 | PREV6 | PROD6 |
|---|---|---|---|---|
| 1 | 1.047838 | 16.54400 | 83.45600 | 0.000000 |
| 2 | 1.063337 | 18.63632 | 81.15426 | 0.209417 |
| 3 | 1.065687 | 18.58649 | 80.79769 | 0.615822 |
| 4 | 1.067716 | 18.52906 | 80.49819 | 0.972751 |
| 5 | 1.069572 | 18.48121 | 80.22625 | 1.292541 |
| 6 | 1.071260 | 18.43802 | 79.97989 | 1.582086 |
| 7 | 1.072795 | 18.39887 | 79.75684 | 1.844297 |
| 8 | 1.074191 | 18.36339 | 79.55476 | 2.081852 |
| 9 | 1.075462 | 18.33124 | 79.37158 | 2.297180 |
| 10 | 1.076618 | 18.30208 | 79.20548 | 2.492447 |

Variance Decomposition of PREV10:

| Period | S.E. | PRIX10 | PREV10 | PROD10 |
|---|---|---|---|---|
| 1 | 1.730393 | 1.148140 | 98.85186 | 0.000000 |
| 2 | 2.097004 | 6.297508 | 76.78148 | 16.92101 |
| 3 | 2.291839 | 5.409836 | 65.68110 | 28.90906 |
| 4 | 2.412775 | 4.884445 | 59.54272 | 35.57283 |
| 5 | 2.483943 | 4.632813 | 56.25770 | 39.10949 |
| 6 | 2.524551 | 4.508505 | 54.49097 | 41.00052 |
| 7 | 2.547398 | 4.444143 | 53.53058 | 42.02528 |
| 8 | 2.560176 | 4.409718 | 53.00382 | 42.58646 |
| 9 | 2.567306 | 4.390952 | 52.71311 | 42.89594 |
| 10 | 2.571282 | 4.380615 | 52.55202 | 43.06736 |

Variance Decomposition of PREV11:

| Period | S.E. | PRIX11 | PREV11 | PROD11 |
|---|---|---|---|---|
| 1 | 5.887587 | 4.893673 | 95.10633 | 0.000000 |
| 2 | 6.354948 | 16.11455 | 81.66602 | 2.219431 |
| 3 | 6.390115 | 16.01861 | 81.51674 | 2.464650 |
| 4 | 6.397775 | 16.16431 | 81.33681 | 2.498879 |
| 5 | 6.398551 | 16.16637 | 81.32888 | 2.504750 |
| 6 | 6.398703 | 16.16874 | 81.32567 | 2.505587 |
| 7 | 6.398721 | 16.16886 | 81.32542 | 2.505724 |
| 8 | 6.398725 | 16.16890 | 81.32535 | 2.505744 |
| 9 | 6.398725 | 16.16891 | 81.32535 | 2.505747 |
| 10 | 6.398725 | 16.16891 | 81.32534 | 2.505748 |

Variance Decomposition of PREV12:

| Period | S.E. | PRIX12 | PREV12 | PROD12 |
|---|---|---|---|---|
| 1 | 2.127976 | 0.000509 | 99.99949 | 0.000000 |
| 2 | 2.250440 | 0.160595 | 89.49742 | 10.34199 |
| 3 | 2.307212 | 0.167862 | 85.87423 | 13.95791 |
| 4 | 2.320873 | 0.170323 | 85.21566 | 14.61401 |
| 5 | 2.323036 | 0.171379 | 85.13095 | 14.69767 |
| 6 | 2.323281 | 0.171540 | 85.12341 | 14.70505 |
| 7 | 2.323300 | 0.171560 | 85.12302 | 14.70542 |
| 8 | 2.323301 | 0.171561 | 85.12302 | 14.70542 |
| 9 | 2.323301 | 0.171561 | 85.12302 | 14.70542 |
| 10 | 2.323301 | 0.171561 | 85.12302 | 14.70542 |

Variance Decomposition of PREV13:

| Period | S.E. | PRIX13 | PREV13 | PROD13 |
|---|---|---|---|---|
| 1 | 5.451362 | 1.389536 | 98.61046 | 0.000000 |
| 2 | 6.225089 | 21.85846 | 77.51335 | 0.628192 |
| 3 | 6.647792 | 19.26278 | 71.26859 | 9.468636 |
| 4 | 6.874150 | 19.43867 | 69.90549 | 10.65584 |
| 5 | 6.882289 | 19.46574 | 69.90356 | 10.63070 |
| 6 | 6.884720 | 19.47542 | 69.87504 | 10.64953 |
| 7 | 6.885024 | 19.47880 | 69.87255 | 10.64865 |
| 8 | 6.885155 | 19.47852 | 69.87105 | 10.65043 |
| 9 | 6.885193 | 19.47869 | 69.87086 | 10.65045 |
| 10 | 6.885194 | 19.47869 | 69.87084 | 10.65048 |

Variance Decomposition of PREV14:

| Period | S.E. | PRIX14 | PREV14 | PROD14 |
|---|---|---|---|---|
| 1 | 1.717295 | 1.052346 | 98.94765 | 0.000000 |
| 2 | 2.572905 | 51.97980 | 47.54523 | 0.474975 |
| 3 | 2.822880 | 58.62754 | 40.96747 | 0.404984 |
| 4 | 2.853056 | 57.43860 | 41.93781 | 0.623585 |
| 5 | 2.876201 | 57.83111 | 41.44305 | 0.725833 |
| 6 | 2.884553 | 58.03123 | 41.24138 | 0.727390 |
| 7 | 2.885541 | 57.99278 | 41.27758 | 0.729638 |
| 8 | 2.886450 | 58.01000 | 41.25834 | 0.731667 |
| 9 | 2.886806 | 58.01876 | 41.24967 | 0.731562 |
| 10 | 2.886849 | 58.01718 | 41.25111 | 0.731715 |

Variance Decomposition of PREV15:

| Period | S.E. | PRIX15 | PREV15 | PROD15 |
|---|---|---|---|---|
| 1 | 2.086302 | 0.777819 | 99.22218 | 0.000000 |
| 2 | 2.828260 | 25.19862 | 70.40123 | 4.400154 |
| 3 | 3.039917 | 27.48512 | 68.16739 | 4.347497 |
| 4 | 3.140992 | 28.67475 | 66.98477 | 4.340482 |
| 5 | 3.187401 | 29.15935 | 66.51788 | 4.322771 |
| 6 | 3.209605 | 29.38760 | 66.29866 | 4.313734 |
| 7 | 3.220264 | 29.49522 | 66.19572 | 4.309059 |
| 8 | 3.225407 | 29.54684 | 66.14639 | 4.306768 |
| 9 | 3.227892 | 29.57169 | 66.12266 | 4.305651 |
| 10 | 3.229094 | 29.58369 | 66.11120 | 4.305109 |

Variance Decomposition of PREV16:

| Period | S.E. | PRIX16 | PREV16 | PROD16 |
|---|---|---|---|---|
| 1 | 1.716897 | 0.041561 | 99.95844 | 0.000000 |
| 2 | 2.293043 | 40.41194 | 56.43272 | 3.155340 |
| 3 | 2.444178 | 36.24843 | 53.94712 | 9.804449 |
| 4 | 2.554910 | 33.91569 | 50.58032 | 15.50399 |
| 5 | 2.640269 | 31.77196 | 48.40348 | 19.82456 |
| 6 | 2.701282 | 30.35380 | 46.82739 | 22.81881 |
| 7 | 2.744861 | 29.40318 | 45.75250 | 24.84432 |
| 8 | 2.775041 | 28.77483 | 45.02143 | 26.20375 |
| 9 | 2.795816 | 28.35723 | 44.52818 | 27.11459 |
| 10 | 2.809995 | 28.07867 | 44.19559 | 27.72574 |

Variance Decomposition of PREV17:

| Period | S.E. | PRIX17 | PREV17 | PROD17 |
|---|---|---|---|---|
| 1 | 3.867914 | 6.176637 | 93.82336 | 0.000000 |
| 2 | 4.508953 | 22.32772 | 77.48903 | 0.183256 |
| 3 | 4.814489 | 27.64515 | 72.08651 | 0.268343 |
| 4 | 4.970544 | 29.99729 | 69.69424 | 0.308463 |
| 5 | 5.052287 | 31.14359 | 68.52813 | 0.328281 |
| 6 | 5.095614 | 31.72897 | 67.93260 | 0.338430 |
| 7 | 5.118715 | 32.03503 | 67.62123 | 0.343739 |
| 8 | 5.131070 | 32.19703 | 67.45642 | 0.346550 |
| 9 | 5.137689 | 32.28333 | 67.36863 | 0.348047 |
| 10 | 5.141238 | 32.32946 | 67.32169 | 0.348847 |

Variance Decomposition of PREV18:

| Period | S.E. | PRIX18 | PREV18 | PROD18 |
|---|---|---|---|---|
| 1 | 2.341020 | 3.308296 | 96.69170 | 0.000000 |
| 2 | 2.819025 | 20.35139 | 78.87912 | 0.769485 |
| 3 | 2.978151 | 25.32072 | 71.16881 | 3.510461 |
| 4 | 3.050815 | 25.25420 | 67.81933 | 6.926462 |
| 5 | 3.100110 | 24.56648 | 65.70568 | 9.727839 |
| 6 | 3.138301 | 24.01212 | 64.26469 | 11.72319 |
| 7 | 3.169399 | 23.61322 | 63.23107 | 13.15571 |
| 8 | 3.195133 | 23.33539 | 62.41709 | 14.24751 |
| 9 | 3.216344 | 23.13031 | 61.74856 | 15.12113 |
| 10 | 3.233739 | 22.96627 | 61.19962 | 15.83410 |

***Slow treatment***

Variance Decomposition of PREV1:

| Period | S.E. | PRIX1 | PREV1 | PROD1 |
|---|---|---|---|---|
| 1 | 2.140506 | 7.868201 | 92.13180 | 0.000000 |
| 2 | 2.806091 | 35.57327 | 62.36051 | 2.066216 |
| 3 | 3.083516 | 41.47129 | 56.01519 | 2.513521 |
| 4 | 3.222151 | 43.87331 | 53.41306 | 2.713632 |
| 5 | 3.293765 | 44.98646 | 52.19929 | 2.814247 |
| 6 | 3.331492 | 45.53984 | 51.59208 | 2.868073 |
| 7 | 3.351579 | 45.82476 | 51.27760 | 2.897632 |
| 8 | 3.362344 | 45.97434 | 51.11162 | 2.914046 |
| 9 | 3.368137 | 46.05376 | 51.02305 | 2.923198 |
| 10 | 3.371265 | 46.09622 | 50.97547 | 2.928305 |

Variance Decomposition of PREV2:

| Period | S.E. | PRIX2 | PREV2 | PROD2 |
|---|---|---|---|---|
| 1 | 2.106346 | 0.001070 | 99.99893 | 0.000000 |
| 2 | 3.485803 | 62.18880 | 37.49122 | 0.319975 |
| 3 | 3.654751 | 61.37350 | 34.10895 | 4.517541 |
| 4 | 3.698163 | 60.15280 | 33.43097 | 6.416238 |
| 5 | 3.715775 | 60.04399 | 33.21532 | 6.740684 |
| 6 | 3.725563 | 60.06443 | 33.06638 | 6.869192 |
| 7 | 3.729635 | 60.04566 | 33.00310 | 6.951236 |
| 8 | 3.731325 | 60.03370 | 32.97805 | 6.988253 |
| 9 | 3.732084 | 60.03000 | 32.96693 | 7.003072 |
| 10 | 3.732427 | 60.02858 | 32.96183 | 7.009595 |

Variance Decomposition of PREV3:

| Period | S.E. | PRIX3 | PREV3 | PROD3 |
|---|---|---|---|---|
| 1 | 3.366270 | 0.739978 | 99.26002 | 0.000000 |
| 2 | 3.696333 | 13.04844 | 86.85258 | 0.098988 |
| 3 | 3.818594 | 16.95252 | 82.93310 | 0.114379 |
| 4 | 3.864498 | 18.28775 | 81.59466 | 0.117585 |
| 5 | 3.882098 | 18.78079 | 81.10071 | 0.118499 |
| 6 | 3.888904 | 18.96872 | 80.91247 | 0.118811 |
| 7 | 3.891544 | 19.04122 | 80.83986 | 0.118927 |
| 8 | 3.892569 | 19.06931 | 80.81172 | 0.118971 |
| 9 | 3.892967 | 19.08022 | 80.80079 | 0.118988 |
| 10 | 3.893122 | 19.08446 | 80.79655 | 0.118995 |

Variance Decomposition of PREV4:

| Period | S.E. | PRIX4 | PREV4 | PROD4 |
|---|---|---|---|---|
| 1 | 2.148455 | 0.246892 | 99.75311 | 0.000000 |
| 2 | 2.834355 | 32.26660 | 59.90029 | 7.833113 |
| 3 | 2.943484 | 37.04345 | 55.54935 | 7.407193 |
| 4 | 2.970215 | 37.98264 | 54.56630 | 7.451063 |
| 5 | 2.978646 | 38.29288 | 54.26725 | 7.439873 |
| 6 | 2.981472 | 38.39894 | 54.16739 | 7.433669 |
| 7 | 2.982396 | 38.43343 | 54.13474 | 7.431827 |
| 8 | 2.982695 | 38.44458 | 54.12416 | 7.431266 |
| 9 | 2.982793 | 38.44820 | 54.12072 | 7.431082 |
| 10 | 2.982825 | 38.44938 | 54.11960 | 7.431022 |

Variance Decomposition of PREV5:

| Period | S.E. | PRIX5 | PREV5 | PROD5 |
|---|---|---|---|---|
| 1 | 2.577465 | 1.597626 | 98.40237 | 0.000000 |
| 2 | 3.212841 | 32.07341 | 67.86300 | 0.063592 |
| 3 | 3.441704 | 39.21746 | 59.60977 | 1.172767 |
| 4 | 3.528376 | 41.15118 | 56.76778 | 2.081038 |
| 5 | 3.561083 | 41.71058 | 55.73411 | 2.555312 |
| 6 | 3.573100 | 41.87813 | 55.36001 | 2.761861 |
| 7 | 3.577402 | 41.92955 | 55.22695 | 2.843504 |
| 8 | 3.578911 | 41.94563 | 55.18042 | 2.873951 |
| 9 | 3.579433 | 41.95074 | 55.16436 | 2.884894 |
| 10 | 3.579611 | 41.95239 | 55.15887 | 2.888734 |

Variance Decomposition of PREV6:

| Period | S.E. | PRIX6 | PREV6 | PROD6 |
|---|---|---|---|---|
| 1 | 2.729569 | 10.55869 | 89.44131 | 0.000000 |
| 2 | 2.867638 | 10.84683 | 88.55904 | 0.594136 |
| 3 | 2.883614 | 10.73308 | 88.56767 | 0.699250 |
| 4 | 2.884194 | 10.74093 | 88.55467 | 0.704396 |
| 5 | 2.884273 | 10.74058 | 88.55393 | 0.705488 |
| 6 | 2.884276 | 10.74066 | 88.55378 | 0.705563 |
| 7 | 2.884276 | 10.74066 | 88.55376 | 0.705574 |
| 8 | 2.884276 | 10.74066 | 88.55376 | 0.705575 |
| 9 | 2.884276 | 10.74066 | 88.55376 | 0.705575 |
| 10 | 2.884276 | 10.74066 | 88.55376 | 0.705575 |

Variance Decomposition of PREV7:

| Period | S.E. | PRIX7 | PREV7 | PROD7 |
|---|---|---|---|---|
| 1 | 3.915445 | 0.008965 | 99.99103 | 0.000000 |
| 2 | 4.050626 | 3.795516 | 95.53829 | 0.666196 |
| 3 | 4.052573 | 3.800207 | 95.47915 | 0.720644 |
| 4 | 4.053287 | 3.826607 | 95.45117 | 0.722224 |
| 5 | 4.053317 | 3.826748 | 95.45040 | 0.722857 |
| 6 | 4.053321 | 3.826894 | 95.45025 | 0.722855 |
| 7 | 4.053321 | 3.826901 | 95.45024 | 0.722860 |
| 8 | 4.053321 | 3.826902 | 95.45024 | 0.722860 |
| 9 | 4.053321 | 3.826902 | 95.45024 | 0.722860 |
| 10 | 4.053321 | 3.826902 | 95.45024 | 0.722860 |

Variance Decomposition of PREV8:

| Period | S.E. | PRIX8 | PREV8 | PROD8 |
|---|---|---|---|---|
| 1 | 5.286313 | 3.40E-05 | 99.99997 | 0.000000 |
| 2 | 7.024697 | 37.51691 | 56.95724 | 5.525847 |
| 3 | 7.102474 | 37.27467 | 56.85191 | 5.873424 |
| 4 | 7.128764 | 37.62239 | 56.53569 | 5.841912 |
| 5 | 7.132005 | 37.66670 | 56.48920 | 5.844095 |
| 6 | 7.132172 | 37.66697 | 56.48917 | 5.843868 |
| 7 | 7.132247 | 37.66802 | 56.48799 | 5.843987 |
| 8 | 7.132249 | 37.66799 | 56.48802 | 5.843990 |
| 9 | 7.132250 | 37.66801 | 56.48800 | 5.843990 |
| 10 | 7.132250 | 37.66802 | 56.48799 | 5.843990 |

Variance Decomposition of PREV9:

| Period | S.E. | PRIX9 | PREV9 | PROD9 |
|---|---|---|---|---|
| 1 | 4.008147 | 0.969187 | 99.03081 | 0.000000 |
| 2 | 4.407121 | 12.92312 | 83.37654 | 3.700340 |
| 3 | 4.456604 | 14.23510 | 81.77845 | 3.986452 |
| 4 | 4.470685 | 14.28388 | 81.57274 | 4.143387 |
| 5 | 4.474015 | 14.40739 | 81.45430 | 4.138309 |
| 6 | 4.474429 | 14.40671 | 81.44879 | 4.144496 |
| 7 | 4.474595 | 14.41008 | 81.44461 | 4.145302 |
| 8 | 4.474618 | 14.41089 | 81.44381 | 4.145306 |
| 9 | 4.474624 | 14.41087 | 81.44375 | 4.145383 |
| 10 | 4.474625 | 14.41092 | 81.44369 | 4.145383 |

Variance Decomposition of PREV10:

| Period | S.E. | PRIX10 | PREV10 | PROD10 |
|---|---|---|---|---|
| 1 | 3.723032 | 0.649038 | 99.35096 | 0.000000 |
| 2 | 5.344410 | 51.26495 | 48.72512 | 0.009932 |
| 3 | 5.346166 | 51.23992 | 48.73352 | 0.026564 |
| 4 | 5.349260 | 51.28502 | 48.68223 | 0.032751 |
| 5 | 5.349347 | 51.28396 | 48.68096 | 0.035085 |
| 6 | 5.349391 | 51.28367 | 48.68046 | 0.035870 |
| 7 | 5.349402 | 51.28352 | 48.68035 | 0.036133 |
| 8 | 5.349406 | 51.28347 | 48.68031 | 0.036221 |
| 9 | 5.349407 | 51.28345 | 48.68030 | 0.036250 |
| 10 | 5.349407 | 51.28344 | 48.68030 | 0.036259 |

Variance Decomposition of PREV11:

| Period | S.E. | PRIX11 | PREV11 | PROD11 |
|---|---|---|---|---|
| 1 | 8.142230 | 0.166486 | 99.83351 | 0.000000 |
| 2 | 9.690806 | 16.69867 | 82.53032 | 0.771011 |
| 3 | 9.979904 | 19.28309 | 79.30545 | 1.411465 |
| 4 | 10.01647 | 19.61822 | 78.81701 | 1.564774 |
| 5 | 10.01916 | 19.63951 | 78.77519 | 1.585302 |
| 6 | 10.01929 | 19.63929 | 78.77408 | 1.586635 |
| 7 | 10.01933 | 19.63936 | 78.77401 | 1.586633 |
| 8 | 10.01934 | 19.63946 | 78.77390 | 1.586640 |
| 9 | 10.01934 | 19.63948 | 78.77387 | 1.586646 |
| 10 | 10.01934 | 19.63948 | 78.77387 | 1.586648 |

Variance Decomposition of PREV12:

| Period | S.E. | PRIX12 | PREV12 | PROD12 |
|---|---|---|---|---|
| 1 | 2.641013 | 12.11758 | 87.88242 | 0.000000 |
| 2 | 2.857461 | 15.41214 | 77.27884 | 7.309020 |
| 3 | 3.068167 | 24.07560 | 67.20438 | 8.720022 |
| 4 | 3.197419 | 29.13160 | 62.53532 | 8.333082 |
| 5 | 3.250084 | 30.91831 | 61.01613 | 8.065555 |
| 6 | 3.264679 | 31.29094 | 60.68018 | 8.028883 |
| 7 | 3.267318 | 31.30349 | 60.63566 | 8.060851 |
| 8 | 3.267851 | 31.29436 | 60.62196 | 8.083677 |
| 9 | 3.268277 | 31.30359 | 60.60617 | 8.090244 |
| 10 | 3.268603 | 31.31454 | 60.59517 | 8.090285 |

Variance Decomposition of PREV13:

| Period | S.E. | PRIX13 | PREV13 | PROD13 |
|---|---|---|---|---|
| 1 | 1.924552 | 3.772666 | 96.22733 | 0.000000 |
| 2 | 2.391076 | 25.36969 | 74.15252 | 0.477797 |
| 3 | 2.569174 | 32.20735 | 67.13799 | 0.654660 |
| 4 | 2.627938 | 34.24101 | 65.05174 | 0.707254 |
| 5 | 2.647072 | 34.87897 | 64.39723 | 0.723795 |
| 6 | 2.653307 | 35.08420 | 64.18668 | 0.729117 |
| 7 | 2.655341 | 35.15087 | 64.11828 | 0.730847 |
| 8 | 2.656005 | 35.17261 | 64.09598 | 0.731410 |
| 9 | 2.656222 | 35.17971 | 64.08870 | 0.731595 |
| 10 | 2.656293 | 35.18203 | 64.08632 | 0.731655 |

Variance Decomposition of PREV14:

| Period | S.E. | PRIX14 | PREV14 | PROD14 |
|---|---|---|---|---|
| 1 | 2.776863 | 2.705264 | 97.29474 | 0.000000 |
| 2 | 2.938375 | 11.12219 | 88.28580 | 0.592012 |
| 3 | 2.968100 | 12.72390 | 86.63011 | 0.645996 |
| 4 | 2.970157 | 12.79046 | 86.56443 | 0.645112 |
| 5 | 2.970261 | 12.78969 | 86.56247 | 0.647834 |
| 6 | 2.970308 | 12.79084 | 86.55973 | 0.649427 |
| 7 | 2.970324 | 12.79115 | 86.55885 | 0.649997 |
| 8 | 2.970328 | 12.79119 | 86.55861 | 0.650193 |
| 9 | 2.970330 | 12.79120 | 86.55854 | 0.650268 |
| 10 | 2.970330 | 12.79120 | 86.55850 | 0.650299 |

Variance Decomposition of PREV15:

| Period | S.E. | PRIX15 | PREV15 | PROD15 |
|---|---|---|---|---|
| 1 | 1.513341 | 3.242705 | 96.75730 | 0.000000 |
| 2 | 1.921059 | 36.90731 | 62.53009 | 0.562602 |
| 3 | 2.117083 | 45.12686 | 51.95253 | 2.920608 |
| 4 | 2.196108 | 45.99943 | 48.34108 | 5.659492 |
| 5 | 2.220091 | 45.70383 | 47.30384 | 6.992329 |
| 6 | 2.225431 | 45.52676 | 47.07839 | 7.394842 |
| 7 | 2.226351 | 45.49196 | 47.04169 | 7.466357 |
| 8 | 2.226568 | 45.49628 | 47.03377 | 7.469944 |
| 9 | 2.226678 | 45.50103 | 47.02952 | 7.469451 |
| 10 | 2.226733 | 45.50227 | 47.02728 | 7.470457 |

Variance Decomposition of PREV16:

| Period | S.E. | PRIX16 | PREV16 | PROD16 |
|---|---|---|---|---|
| 1 | 4.213536 | 25.76761 | 74.23239 | 0.000000 |
| 2 | 5.512436 | 41.36442 | 49.58831 | 9.047264 |
| 3 | 6.162156 | 42.13638 | 42.40439 | 15.45924 |
| 4 | 6.482643 | 41.47192 | 39.86594 | 18.66214 |
| 5 | 6.642783 | 41.00828 | 38.80630 | 20.18542 |
| 6 | 6.723964 | 40.76404 | 38.31213 | 20.92383 |
| 7 | 6.765544 | 40.64070 | 38.06787 | 21.29143 |
| 8 | 6.786963 | 40.57817 | 37.94396 | 21.47787 |
| 9 | 6.798029 | 40.54618 | 37.88039 | 21.57343 |
| 10 | 6.803753 | 40.52971 | 37.84762 | 21.62267 |

Variance Decomposition of PREV17:

| Period | S.E. | PRIX17 | PREV17 | PROD17 |
|---|---|---|---|---|
| 1 | 1.739459 | 2.645899 | 97.35410 | 0.000000 |
| 2 | 2.788153 | 61.68039 | 37.94727 | 0.372336 |
| 3 | 2.974390 | 65.30383 | 33.64104 | 1.055133 |
| 4 | 3.058806 | 66.80696 | 31.88092 | 1.312120 |
| 5 | 3.093324 | 67.35381 | 31.20846 | 1.437732 |
| 6 | 3.108082 | 67.58222 | 30.92730 | 1.490476 |
| 7 | 3.114381 | 67.67837 | 30.80857 | 1.513068 |
| 8 | 3.117079 | 67.71937 | 30.75792 | 1.522713 |
| 9 | 3.118236 | 67.73691 | 30.73625 | 1.526843 |
| 10 | 3.118732 | 67.74442 | 30.72697 | 1.528613 |

Variance Decomposition of PREV18:

| Period | S.E. | PRIX18 | PREV18 | PROD18 |
|---|---|---|---|---|
| 1 | 2.167422 | 1.185013 | 98.81499 | 0.000000 |
| 2 | 3.350342 | 40.95020 | 46.08073 | 12.96907 |
| 3 | 3.386199 | 40.11418 | 45.15208 | 14.73374 |
| 4 | 3.393337 | 39.96410 | 44.96571 | 15.07018 |
| 5 | 3.394295 | 39.94208 | 44.94039 | 15.11752 |
| 6 | 3.394434 | 39.93882 | 44.93672 | 15.12446 |
| 7 | 3.394453 | 39.93838 | 44.93621 | 15.12541 |
| 8 | 3.394456 | 39.93832 | 44.93614 | 15.12555 |
| 9 | 3.394456 | 39.93831 | 44.93613 | 15.12556 |
| 10 | 3.394456 | 39.93831 | 44.93613 | 15.12557 |

***Divergent treatment***

Variance Decomposition of PREV1:

| Period | S.E. | PRIX1 | PREV1 | PROD1 |
|---|---|---|---|---|
| 1 | 5.436234 | 0.728781 | 99.27122 | 0.000000 |
| 2 | 6.011093 | 0.697729 | 98.70479 | 0.597481 |
| 3 | 6.147218 | 0.671244 | 98.40431 | 0.924443 |
| 4 | 6.186551 | 0.675099 | 98.25488 | 1.070025 |
| 5 | 6.199013 | 0.680273 | 98.19220 | 1.127524 |
| 6 | 6.203144 | 0.682932 | 98.16817 | 1.148899 |
| 7 | 6.204544 | 0.684032 | 98.15937 | 1.156597 |
| 8 | 6.205024 | 0.684448 | 98.15623 | 1.159323 |
| 9 | 6.205189 | 0.684600 | 98.15512 | 1.160280 |
| 10 | 6.205247 | 0.684653 | 98.15473 | 1.160614 |

Variance Decomposition of PREV2:

| Period | S.E. | PRIX2 | PREV2 | PROD2 |
|---|---|---|---|---|
| 1 | 2.325864 | 1.759831 | 98.24017 | 0.000000 |
| 2 | 4.380158 | 71.27347 | 28.62938 | 0.097145 |
| 3 | 4.501438 | 71.07227 | 28.68268 | 0.245049 |
| 4 | 4.597903 | 72.07007 | 27.67998 | 0.249952 |
| 5 | 4.614643 | 72.14987 | 27.59149 | 0.258639 |
| 6 | 4.622390 | 72.21706 | 27.52310 | 0.259835 |
| 7 | 4.624310 | 72.22949 | 27.51000 | 0.260509 |
| 8 | 4.625018 | 72.23513 | 27.50421 | 0.260661 |
| 9 | 4.625221 | 72.23656 | 27.50272 | 0.260721 |
| 10 | 4.625289 | 72.23708 | 27.50218 | 0.260737 |

Variance Decomposition of PREV3:

| Period | S.E. | PRIX3 | PREV3 | PROD3 |
|---|---|---|---|---|
| 1 | 8.895731 | 15.97559 | 84.02441 | 0.000000 |
| 2 | 10.52045 | 11.60395 | 88.00396 | 0.392086 |
| 3 | 11.27777 | 10.43049 | 88.42516 | 1.144347 |
| 4 | 11.76936 | 9.847348 | 87.82377 | 2.328884 |
| 5 | 12.08049 | 9.472419 | 87.50649 | 3.021088 |
| 6 | 12.27607 | 9.239891 | 87.37356 | 3.386551 |
| 7 | 12.40018 | 9.097382 | 87.30376 | 3.598855 |
| 8 | 12.47955 | 9.008908 | 87.25997 | 3.731119 |
| 9 | 12.53053 | 8.953122 | 87.23160 | 3.815275 |
| 10 | 12.56332 | 8.917599 | 87.21338 | 3.869018 |

Variance Decomposition of PREV4:

| Period | S.E. | PRIX4 | PREV4 | PROD4 |
|---|---|---|---|---|
| 1 | 1.718021 | 11.02077 | 88.97923 | 0.000000 |
| 2 | 4.799794 | 87.98828 | 11.86615 | 0.145564 |
| 3 | 5.052220 | 86.36784 | 11.88752 | 1.744640 |
| 4 | 5.424247 | 85.81465 | 10.58866 | 3.596696 |
| 5 | 5.621906 | 83.91219 | 10.09298 | 5.994828 |
| 6 | 5.807540 | 82.02801 | 9.581726 | 8.390267 |
| 7 | 5.961731 | 80.04775 | 9.186704 | 10.76554 |
| 8 | 6.103138 | 78.17989 | 8.834176 | 12.98593 |
| 9 | 6.231714 | 76.43125 | 8.529001 | 15.03975 |
| 10 | 6.350867 | 74.83092 | 8.258247 | 16.91084 |

Variance Decomposition of PREV5:

| Period | S.E. | PRIX5 | PREV5 | PROD5 |
|---|---|---|---|---|
| 1 | 4.775001 | 0.546653 | 99.45335 | 0.000000 |
| 2 | 7.939971 | 63.55224 | 36.41905 | 0.028711 |
| 3 | 8.046254 | 64.24573 | 35.60647 | 0.147798 |
| 4 | 8.075601 | 64.41353 | 35.34851 | 0.237961 |
| 5 | 8.078138 | 64.37715 | 35.32630 | 0.296553 |
| 6 | 8.079606 | 64.36340 | 35.31394 | 0.322666 |
| 7 | 8.080803 | 64.36348 | 35.30377 | 0.332744 |
| 8 | 8.081476 | 64.36582 | 35.29806 | 0.336122 |
| 9 | 8.081785 | 64.36743 | 35.29544 | 0.337134 |
| 10 | 8.081905 | 64.36818 | 35.29442 | 0.337405 |

Variance Decomposition of PREV6:

| Period | S.E. | PRIX6 | PREV6 | PROD6 |
|---|---|---|---|---|
| 1 | 2.422996 | 0.001901 | 99.99810 | 0.000000 |
| 2 | 4.850698 | 73.31318 | 25.29001 | 1.396810 |
| 3 | 5.157652 | 72.16982 | 23.10188 | 4.728303 |
| 4 | 5.456099 | 72.18774 | 20.73973 | 7.072531 |
| 5 | 5.619496 | 71.46406 | 19.62300 | 8.912943 |
| 6 | 5.737335 | 70.98960 | 18.85681 | 10.15360 |
| 7 | 5.816536 | 70.61734 | 18.36795 | 11.01471 |
| 8 | 5.871991 | 70.36157 | 18.03602 | 11.60241 |
| 9 | 5.910555 | 70.18161 | 17.81060 | 12.00779 |
| 10 | 5.937576 | 70.05681 | 17.65515 | 12.28804 |

Variance Decomposition of PREV7:

| Period | S.E. | PRIX7 | PREV7 | PROD8 |
|---|---|---|---|---|
| 1 | 2.722427 | 1.055912 | 98.94409 | 0.000000 |
| 2 | 3.900668 | 49.49655 | 48.48065 | 2.022800 |
| 3 | 4.344668 | 56.71729 | 39.14454 | 4.138176 |
| 4 | 4.551075 | 58.10776 | 35.77141 | 6.120838 |
| 5 | 4.674061 | 58.17764 | 34.01902 | 7.803335 |
| 6 | 4.758932 | 57.92574 | 32.91248 | 9.161779 |
| 7 | 4.821944 | 57.62557 | 32.13907 | 10.23536 |
| 8 | 4.870423 | 57.35378 | 31.56874 | 11.07749 |
| 9 | 4.908394 | 57.12705 | 31.13556 | 11.73739 |
| 10 | 4.938414 | 56.94371 | 30.80085 | 12.25544 |

Variance Decomposition of PREV8:

| Period | S.E. | PRIX8 | PREV8 | PROD8 |
|---|---|---|---|---|
| 1 | 2.872735 | 6.393453 | 93.60655 | 0.000000 |
| 2 | 3.787024 | 44.47754 | 55.05417 | 0.468298 |
| 3 | 4.097184 | 52.10185 | 47.14867 | 0.749474 |
| 4 | 4.184502 | 53.80014 | 45.23761 | 0.962250 |
| 5 | 4.208589 | 54.13876 | 44.73757 | 1.123671 |
| 6 | 4.215601 | 54.15993 | 44.59726 | 1.242814 |
| 7 | 4.218173 | 54.12325 | 44.54762 | 1.329130 |
| 8 | 4.219578 | 54.08811 | 44.52079 | 1.391098 |
| 9 | 4.220597 | 54.06346 | 44.50111 | 1.435431 |
| 10 | 4.221398 | 54.04746 | 44.48541 | 1.467123 |

Variance Decomposition of PREV9:

| Period | S.E. | PRIX9 | PREV9 | PROD9 |
|---|---|---|---|---|
| 1 | 3.109291 | 1.235546 | 98.76445 | 0.000000 |
| 2 | 4.106097 | 43.07242 | 56.73648 | 0.191098 |
| 3 | 4.288764 | 43.93662 | 53.60655 | 2.456823 |
| 4 | 4.398211 | 44.39660 | 51.07098 | 4.532422 |
| 5 | 4.451583 | 43.84905 | 49.89452 | 6.256433 |
| 6 | 4.481366 | 43.39709 | 49.23420 | 7.368709 |
| 7 | 4.497514 | 43.09862 | 48.88201 | 8.019368 |
| 8 | 4.506014 | 42.93618 | 48.70086 | 8.362959 |
| 9 | 4.510309 | 42.85753 | 48.61159 | 8.530882 |
| 10 | 4.512379 | 42.82332 | 48.56978 | 8.606905 |

Variance Decomposition of PREV10:

| Period | S.E. | PRIX10 | PREV10 | PROD10 |
|---|---|---|---|---|
| 1 | 3.451855 | 6.579376 | 93.42062 | 0.000000 |
| 2 | 4.070770 | 14.70202 | 78.38639 | 6.911594 |
| 3 | 4.588205 | 31.16437 | 63.02415 | 5.811473 |
| 4 | 4.928926 | 40.28758 | 54.65118 | 5.061241 |
| 5 | 5.093202 | 43.91629 | 51.20784 | 4.875870 |
| 6 | 5.154623 | 45.06372 | 50.05351 | 4.882771 |
| 7 | 5.172404 | 45.32963 | 49.75502 | 4.915348 |
| 8 | 5.176183 | 45.36154 | 49.70459 | 4.933877 |
| 9 | 5.176729 | 45.35771 | 49.70208 | 4.940211 |
| 10 | 5.176841 | 45.35655 | 49.70202 | 4.941431 |

Variance Decomposition of PREV11:

| Period | S.E. | PRIX11 | PREV11 | PROD11 |
|---|---|---|---|---|
| 1 | 3.245513 | 18.22193 | 81.77807 | 0.000000 |
| 2 | 4.649928 | 20.54032 | 75.48064 | 3.979039 |
| 3 | 5.358581 | 21.16142 | 74.39319 | 4.445383 |
| 4 | 5.798838 | 21.49592 | 73.81112 | 4.692962 |
| 5 | 6.080969 | 21.69227 | 73.48865 | 4.819076 |
| 6 | 6.266362 | 21.81500 | 73.29209 | 4.892912 |
| 7 | 6.389765 | 21.89400 | 73.16765 | 4.938350 |
| 8 | 6.472578 | 21.94580 | 73.08686 | 4.967343 |
| 9 | 6.528440 | 21.98017 | 73.03357 | 4.986255 |
| 10 | 6.566249 | 22.00316 | 72.99806 | 4.998772 |

Variance Decomposition of PREV12:

| Period | S.E. | PRIX12 | PREV12 | PROD12 |
|---|---|---|---|---|
| 1 | 2.571166 | 15.52486 | 84.47514 | 0.000000 |
| 2 | 3.829032 | 58.58954 | 41.40783 | 0.002627 |
| 3 | 4.225727 | 64.22071 | 35.73653 | 0.042758 |
| 4 | 4.401225 | 66.22115 | 33.68501 | 0.093842 |
| 5 | 4.480929 | 67.02475 | 32.83981 | 0.135440 |
| 6 | 4.517955 | 67.37251 | 32.46422 | 0.163272 |
| 7 | 4.535321 | 67.52808 | 32.29190 | 0.180024 |
| 8 | 4.543509 | 67.59897 | 32.21158 | 0.189452 |
| 9 | 4.547380 | 67.63164 | 32.17384 | 0.194522 |
| 10 | 4.549213 | 67.64681 | 32.15603 | 0.197163 |

Variance Decomposition of PREV13:

| Period | S.E. | PRIX13 | PREV13 | PROD13 |
|---|---|---|---|---|
| 1 | 6.395603 | 2.620175 | 97.37983 | 0.000000 |
| 2 | 8.456804 | 10.14822 | 68.56560 | 21.28618 |
| 3 | 8.683276 | 9.652739 | 68.15264 | 22.19462 |
| 4 | 8.787454 | 9.499707 | 67.43184 | 23.06845 |
| 5 | 8.814047 | 9.443392 | 67.29302 | 23.26359 |
| 6 | 8.823657 | 9.423878 | 67.23114 | 23.34498 |
| 7 | 8.826623 | 9.417604 | 67.21314 | 23.36926 |
| 8 | 8.827623 | 9.415503 | 67.20676 | 23.37774 |
| 9 | 8.827946 | 9.414819 | 67.20473 | 23.38045 |
| 10 | 8.828053 | 9.414593 | 67.20405 | 23.38136 |

Variance Decomposition of PREV16:

| Period | S.E. | PRIX16 | PREV16 | PROD16 |
|---|---|---|---|---|
| 1 | 2.935281 | 3.919463 | 96.08054 | 0.000000 |
| 2 | 4.126629 | 15.59813 | 84.28297 | 0.118896 |
| 3 | 4.904370 | 20.55418 | 79.27157 | 0.174252 |
| 4 | 5.443172 | 22.96226 | 76.83723 | 0.200505 |
| 5 | 5.832003 | 24.30647 | 75.47896 | 0.214573 |
| 6 | 6.120060 | 25.13557 | 74.64150 | 0.222932 |
| 7 | 6.337114 | 25.68305 | 74.08866 | 0.228293 |
| 8 | 6.502533 | 26.06188 | 73.70619 | 0.231923 |
| 9 | 6.629601 | 26.33276 | 73.43276 | 0.234480 |
| 10 | 6.727761 | 26.53106 | 73.23261 | 0.236332 |

Variance Decomposition of PREV14:

| Period | S.E. | PRIX14 | PREV14 | PROD14 |
|---|---|---|---|---|
| 1 | 3.631420 | 8.705210 | 91.29479 | 0.000000 |
| 2 | 5.221491 | 50.34043 | 49.65523 | 0.004343 |
| 3 | 5.403935 | 52.74134 | 46.63728 | 0.621384 |
| 4 | 5.457931 | 51.95255 | 46.31212 | 1.735326 |
| 5 | 5.498425 | 51.80762 | 45.68401 | 2.508373 |
| 6 | 5.512898 | 51.59453 | 45.44910 | 2.956371 |
| 7 | 5.521691 | 51.43460 | 45.30981 | 3.255583 |
| 8 | 5.528554 | 51.31257 | 45.19745 | 3.489984 |
| 9 | 5.533982 | 51.21202 | 45.10927 | 3.678713 |
| 10 | 5.538221 | 51.13414 | 45.04056 | 3.825299 |

Variance Decomposition of PREV17:

| Period | S.E. | PRIX17 | PREV17 | PROD17 |
|---|---|---|---|---|
| 1 | 3.970909 | 0.051509 | 99.94849 | 0.000000 |
| 2 | 11.58966 | 88.07048 | 11.73679 | 0.192731 |
| 3 | 11.99417 | 88.69885 | 11.10881 | 0.192338 |
| 4 | 12.00018 | 88.69789 | 11.10890 | 0.193215 |
| 5 | 12.00899 | 88.71314 | 11.09286 | 0.194006 |
| 6 | 12.00931 | 88.71331 | 11.09251 | 0.194181 |
| 7 | 12.00934 | 88.71333 | 11.09246 | 0.194209 |
| 8 | 12.00936 | 88.71334 | 11.09244 | 0.194219 |
| 9 | 12.00936 | 88.71334 | 11.09244 | 0.194221 |
| 10 | 12.00936 | 88.71334 | 11.09244 | 0.194221 |

Variance Decomposition of PREV15:

| Period | S.E. | PRIX15 | PREV15 | PROD15 |
|---|---|---|---|---|
| 1 | 4.679279 | 4.852705 | 95.14729 | 0.000000 |
| 2 | 6.451423 | 31.50141 | 64.26102 | 4.237571 |
| 3 | 7.320458 | 37.55997 | 56.20591 | 6.234125 |
| 4 | 7.708767 | 40.40049 | 53.78943 | 5.810084 |
| 5 | 7.924003 | 41.67402 | 52.54788 | 5.778104 |
| 6 | 8.039209 | 42.34213 | 51.93599 | 5.721884 |
| 7 | 8.102849 | 42.69345 | 51.60672 | 5.699831 |
| 8 | 8.137900 | 42.88461 | 51.42917 | 5.686223 |
| 9 | 8.157318 | 42.98921 | 51.33168 | 5.679109 |
| 10 | 8.168079 | 43.04690 | 51.27798 | 5.675115 |

Variance Decomposition of PREV18:

| Period | S.E. | PRIX18 | PREV18 | PROD18 |
|---|---|---|---|---|
| 1 | 5.299448 | 3.640679 | 96.35932 | 0.000000 |
| 2 | 5.928872 | 2.968562 | 94.58088 | 2.450555 |
| 3 | 6.216897 | 4.255414 | 89.93553 | 5.809054 |
| 4 | 6.429441 | 6.197968 | 84.97291 | 8.829120 |
| 5 | 6.597328 | 7.978815 | 80.90654 | 11.11465 |
| 6 | 6.725374 | 9.364470 | 77.90227 | 12.73326 |
| 7 | 6.819701 | 10.37372 | 75.77316 | 13.85312 |
| 8 | 6.887637 | 11.08841 | 74.28834 | 14.62325 |
| 9 | 6.935914 | 11.58855 | 73.25836 | 15.15308 |
| 10 | 6.969962 | 11.93696 | 72.54452 | 15.51852 |

- **Instructions (French):**

As an example, these are the instructions for treatment *slow* (in French).

**Bienvenue**

L’expérience à laquelle vous allez participer est destinée à l’étude de la prise de décision. Si vous suivez les instructions et que vous prenez les bonnes décisions, vous pouvez gagner une somme d’argent non-négligeable. Toutes vos réponses seront traitées de façon anonyme et seront recueillies au travers d’un réseau informatique. Vous indiquerez vos choix à l’ordinateur devant lequel vous êtes assis et celui-ci vous communiquera les informations sur le déroulement du jeu et sur l’évolution des gains.

La somme totale d'argent gagnée pendant l'expérience vous sera versée, en liquide, à la fin de celle-ci. Lorsque tous les participants auront pris connaissance des instructions, une description générale sera effectuée à voix haute.

**Cadre général de l'expérience**

L'expérience comporte 40 périodes. 18 personnes participent à cette expérience y compris vous-même. Les 18 personnes sont réparties en trois groupes indépendants de 6 personnes chacun. Ces trois groupes resteront les mêmes tout au long des 40 périodes. Vous avez été affecté par tirage au sort à l'un des trois groupes. Vous ne connaissez pas l'identité des 5 autres personnes de votre groupe, et les autres membres de votre groupe ne connaissent pas votre identité. Dans votre groupe, chaque membre est indexé par une lettre : A, B, C, D, E, F. Vous êtes le membre A.

Au début de l'expérience, vous disposerez d'un capital de 100 000 points. A chacune des 40 périodes de l'expérience, vous allez soit réaliser un gain, soit subir une perte. Les points gagnés seront ajoutés à votre capital de départ et les points perdus y seront retranchés.

**A chaque période vous serez amené à prendre deux décisions** :

-une décision de production

-une prévision de prix

Votre gain ou perte de chaque période sera composé de deux éléments :

-un gain ou une perte résultant de votre décision de production

-un gain ou une perte résultant de votre prévision

Votre perte ou votre gain à chaque période dépendra de vos décisions et des décisions des autres membres de votre groupe. Plus précisément, le gain ou la perte issu(e) de votre décision de production dépendra non seulement de votre propre décision de production, mais aussi des décisions de production des autres membres de votre groupe. Par contre, le gain ou la perte lié(e) à votre décision de production ne sera pas affecté(e) par votre prévision de prix. En revanche, le gain ou la perte de votre prévision de prix dépendra de l'ensemble des décisions de production.

La façon de calculer les gains et les pertes sera explicitée dans la suite des instructions.

A la fin de l'expérience, vos points disponibles (pertes déduites et gains rajoutés) seront convertis en Euros. La procédure de conversion sera détaillée à la fin des instructions.

**La décision de production**

Au début de chaque période, vous devez décider d'une quantité à produire. Au même moment, chaque membre de votre groupe doit décider également d'une quantité à produire. Les décisions de production des 5 joueurs du groupe forment la **quantité totale produite.** Cette quantité totale produite **sera vendue sur le marché**. Au moment de prendre votre décision de production, vous ne connaissez pas le prix de vente. De même, les autres membres de votre groupe ne connaîtront pas le prix de vente. Par contre, vous connaîtrez votre coût de production, qui est retracé dans le tableau 1. Ce tableau est le même pour tous les membres de votre groupe.

NB. L'expression « nup » signifie « nombre d'unités produites ».

Tableau 1 : **Coûts de production**

| Numéro de l'intervalle | Intervalles de production | *Coût de production de chaque unité supplémentaire produite* | *Coût total de production* |
|---|---|---|---|
| 1 | de 1 à 8 | 20 | nup $\times$ 20 |
| 2 | de 9 à 16 | 25 | (nup - 8) $\times$ 25 + 160 |
| 3 | de 17 à 24 | 30 | (nup -16) $\times$ 30 + 360 |
| 4 | de 25 à 32 | 35 | (nup - 24) $\times$ 35 + 600 |
| 5 | de 33 à 40 | 40 | (nup - 32) $\times$40 + 880 |
| 6 | de 41 à 48 | 45 | (nup - 40) $\times$45 + 1200 |
| 7 | de 49 à 56 | 50 | (nup - 48) $\times$50 + 1560 |
| 8 | de 57 à 64 | 55 | (nup - 56) $\times$ 55 + 1960 |
| 9 | de 65 à 72 | 60 | (nup - 64) $\times$ 60 + 2400 |
| 10 | de 73 à 80 | 65 | (nup - 72) $\times$65 + 2880 |
| 11 | de 81 à 88 | 70 | (nup - 80) $\times$70 + 3400 |
| 12 | de 89 à 96 | 75 | (nup - 88) $\times$75 + 3960 |
| 13 | de 97 à 104 | 80 | (nup - 96) $\times$80 + 4560 |
| 14 | de 105 à 112 | 85 | (nup - 104) $\times$85 + 5200 |
| 15 | de 113 à 120 | 90 | (nup - 112) $\times$90 + 5880 |
| 16 | de 121 à 128 | 95 | (nup - 120) $\times$95 + 6600 |
| 17 | de 129 à 136 | 100 | (nup - 128) $\times$100 + 7360 |
| 18 | de 137 à 144 | 105 | (nup - 136) $\times$105 + 8160 |
| 19 | de 145 à 152 | 110 | (nup - 144) $\times$110 + 9000 |
| 20 | de 153 à 160 | 115 | (nup - 152) $\times$115 + 9880 |
| 21 | de 161 à plus | 120 | (nup - 160) $\times$120 + 10800 |

La première colonne du tableau 1 indique le numéro de l'intervalle de production dans lequel vous vous situez. Ces intervalles de production sont détaillés dans la deuxième colonne du tableau. Par exemple, si vous produisez 15 unités, vous vous situez dans l'intervalle 2.

Notez que le coût de production unitaire est différent pour chaque intervalle. Ceci est indiqué dans la troisième colonne. Ainsi chacune des 8 premières unités (intervalle 1) vous coûte 20 points ; chacune des unités de 9 à 16 (intervalle 2) vous coûte 25 points ; chacune des unités de 17 à 24 (intervalle 3) vous coûte 30 points etc.…

La dernière colonne du tableau retrace les règles de calcul de vos coûts de production totaux pour chaque intervalle de production.

La lecture de ce tableau est simple. Nous allons l'illustrer à l'aide de trois exemples.

*Exemple 1 :*

Supposons que vous décidiez de produire nup = 5. Vous vous situez alors dans l'intervalle de production numéro 1 (entre 0 et 8 unités). Chacune de vos 5 unités produites vous coûte alors 20 points. Votre coût total de production pour les 5 unités est alors égal à $5 \times 20 = 100$ points.

*Exemple 2 :*

Supposons que vous décidiez de produire nup = 9. Les 8 premières unités produites correspondent à l'intervalle de production numéro 1 et la $9^{ème}$ unité correspond à l'intervalle de production numéro 2. Les 8 premières unités vous coûtent donc 20 points chacune et la $9^{ème}$ unité vous coûte 25 points. Votre coût total de production pour ces 9 unités est donc de $(8 \times 20) + (1 \times 25) = 160 + 25 = 185$ points.

*Exemple 3 :*

Supposons que vous décidiez de produire nup = 26. Pour connaître le coût total de votre production, vous devez faire le calcul suivant : les 8 premières unités vous coûtent chacune 20 points, soit $8 \times 20 = 160$ points au total. Les 8 unités suivantes (de la 9ème à la 16ème incluses ) vous coûtent chacune 25 points, soit $8 \times 25 = 200$ points au total. Les 16 premières unités coûtent donc 160 + 200 = 360 points. Les 8 unités suivantes (de 17 à 24 incluses) coûtent chacune 30 points, soit $8 \times 30 = 240$ points au total. Donc les 24 unités coûtent 160 + 200 + 240 = 600 points au total. Finalement les 2 dernières unités (25 et 26) vous coûtent chacune 35 points, soit $2 \times 35 = 70$ points au total. Donc le coût total de vos 26 unités s'élève à (160 + 200 + 240) + 70 = 670 points.

Vous n'avez pas besoin de faire tous ces calculs, car la dernière colonne du tableau vous indique les formules permettant d'obtenir le coût total directement. Il suffit de remplacer *nup* par la quantité que vous voulez produire dans l'intervalle correspondant. Par exemple, si vous voulez produire 26 unités comme dans l'exemple précédent, votre coût total sera calculé en vous reportant à l'intervalle numéro 4 et en remplaçant dans la formule *nup* par 26 soit $(26 - 24) \times 35 + 600 = 670$.

**Fixation du prix de vente auquel vous vendez votre production**

A chaque période, le prix de vente auquel vous pouvez écouler votre production ne dépend pas de votre production individuelle. Le prix de vente dépendra uniquement des décisions de production des autres membres de votre groupe pour cette période (c'est-à-dire de la **quantité totale produite par les autres 5 membres de votre groupe : B, C, D, E, F**). Le prix de vente dépend de la quantité totale produite selon une grille fixée par les acheteurs, décrite dans le tableau numéro 2.

Tableau 2 : **Grille de prix de vente en fonction de la production totale**

| *Numéro de l'intervalle* | *Quantités totales produites par les 5 autres membres de votre groupe* | *Prix de vente unitaire* |
|---|---|---|
| 1 | de 1 à 44 | 100 |
| 2 | de 45 à 89 | 95 |
| 3 | de 90 à 134 | 90 |
| 4 | de 135 à 179 | 85 |
| 5 | de 180 à 224 | 80 |
| 6 | de 225 à 269 | 75 |
| 7 | de 270 à 314 | 70 |
| 8 | de 315 à 359 | 65 |
| 9 | de 360 à 404 | 60 |
| 10 | de 405 à 449 | 55 |
| 11 | de 450 à 494 | 50 |
| 12 | de 495 à 539 | 45 |
| 13 | de 540 à 584 | 40 |
| 14 | de 585 à 629 | 35 |
| 15 | de 630 à 674 | 30 |
| 16 | de 675 à 719 | 25 |
| 17 | de 720 à 764 | 20 |
| 18 | de 765 à 809 | 15 |
| 19 | de 810 à 854 | 10 |
| 20 | de 855 à 899 | 5 |
| 21 | 900 et plus | 0 |

La première colonne de ce tableau précise chacun des intervalles de production totale. La deuxième détaille ces intervalles. La dernière colonne indique le prix unitaire auquel chacune de vos unités sera vendue. **Toutes vos unités produites seront vendues au même prix.**

Par exemple, si la production totale des 5 autres membres de votre groupe est de 486 unités, chacune de vos unités sera vendue au prix de 50 points l'unité. Si, par exemple, vous avez produit 97 unités, votre recette sera égale à $97 \times 50 = 4850$ points. Pour connaître votre gain ou votre perte il faudra retrancher le coût de production à cette recette.

Le prix de 50 points par unité s'appliquera uniquement à votre production. Le prix de vente auquel font face les autres membres de votre groupe sera déterminé selon les mêmes règles de calcul.

**Fixation du prix de vente auquel vendent leurs productions les joueurs B, C, D, E et F**

La quantité que vous décidez de produire à chaque période rentre dans le calcul du prix de vente auquel vendent leurs productions les autres joueurs. Ces prix de vente s'établissent selon la même grille de prix que pour votre production, **à la différence que la production totale qui détermine ce prix de vente est calculée d'une autre manière**.

*Rappel* : votre prix de vente est déterminé par la grille de prix précédente en fonction de la quantité totale produite par les membres B, C, D, E et F.

Le prix de vente pour **B** est déterminé par la même grille de prix en fonction de la **quantité totale produite par les membres A (vous-même), C, D, E, et F**.

Le prix de vente pour **C** est déterminé par la même grille de prix en fonction de la **quantité totale produite par les membres A (vous-même), B, D, E, et F.**

Le prix de vente pour **D** est déterminé par la même grille de prix en fonction de la **quantité totale produite par les membres A (vous-même), B, C, E, et F.**

Le prix de vente pour **E** est déterminé par la même grille de prix en fonction de la **quantité totale produite par les membres A (vous-même), B, C, D et F.**

Le prix de vente pour **F** est déterminé par la même grille de prix en fonction de la **quantité totale produite par les membres A (vous-même), B, C, D et E.**

**Le gain ou la perte de votre décision de production**

Le profit de votre production est calculé selon la règle suivante :

**Votre profit pour la période en cours = votre quantité produite ´ prix pour cette période – votre coût total de production.**

Prenons quelques exemples pour illustrer cette règle.

*Exemple 1 :*

Supposons que vous décidiez de produire nup = 53 unités et que les autres membres de votre groupe produisent ensemble 325 unités. Pour cette quantité, le prix auquel de vente est de 65 points par unité. Votre recette est donc égale à $53 \times 65 = 3445$ points.

Votre coût total de production est calculé en appliquant les formules du tableau 1 (intervalle numéro 7) : $(53 - 48) \times 50 + 1560 = 1810$ points.

**Votre profit** pour cette période est donc de $3445 - 1810 = 1735$ points. Ce profit s'ajoute à votre capital disponible en début de période.

*Exemple 2 :*

Supposons que vous décidiez de produire nup = 53 unités et que les autres membres de votre groupe produisent ensemble 653 unités. Pour cette quantité, le prix de vente est de 30 points par unité. Votre recette est donc de $53 \times 30 = 1590$ points.

Votre coût total de production est de : $(53 - 48) \times 50 + 1560 = 1810$ points.

**Votre perte** pour cette période est donc de $1590 - 1810 = - 220$ points. Cette perte sera retranchée à votre capital disponible en début de période.

*Exemple 3 :*

Supposons que vous décidiez de produire nup = 53 unités et que les autres membres de votre groupe produisent ensemble 853 unités. Pour cette quantité, le prix de vente est de 10 points par unité. Votre recette est donc égale à $53 \times 10 = 530$ points.

Calculons votre coût total de production : $(53 - 48) \times 50 + 1560 = 1810$ points.

**Votre perte** pour cette période est donc de 530 - 1810= - 1280 points. Cette perte sera retranchée à votre capital disponible en début de période.

**Votre prévision et le gain ou la perte lié à cette prévision**

A chaque période, en plus de votre décision de production, vous devez faire une prévision du prix de vente de la production du groupe. Votre prévision vous fait gagner des points supplémentaires lorsqu'elle est « bonne » et perdre des points supplémentaires lorsqu'elle est « mauvaise ».

Si vous ne faites aucune erreur de prévision, c'est-à-dire si vous devinez exactement le prix de vente de la production, vous gagnerez 1000 points. Si vous faites une erreur de prévision, des points seront déduits de cette somme. Le nombre de points déduits sera calculé en fonction de votre erreur selon la formule suivante :

Gain ou perte de la prévision = $1000 - 0{,}8 \times$ (prix prévu – prix établi sur le marché)²

L'erreur se calcule donc en comparant votre prévision de prix au prix qui s'établit sur le marché. Plus votre prévision de prix est proche du prix effectivement réalisé sur le marché, plus vous gagnerez des points supplémentaires.

Comparons deux cas : dans le premier cas, vous prévoyez un prix de 90 points et le prix de vente est de 40 points. Votre perte liée à la prévision sera de : $1000 - 0{,}8 \times (90 - 40)^2 = - 1000$.

Dans le deuxième cas, vous prévoyez un prix de 80 points et le prix qui s'établit sur le marché est de 100 points. Avec la règle de calcul précédente, votre gain dans le deuxième cas sera $1000 - 0{,}8 \times (80 - 100)^2 = 680$ (les valeurs indiquées sont plus proches dans le deuxième cas).

**La règle de calcul de votre gain ou perte lié à la prévision est telle que vous avez toujours intérêt à annoncer votre vraie prévision.**

**Récapitulatif**

L'expérience consiste en une succession de 40 périodes au cours desquelles vous devez choisir une quantité à produire et faire une prévision du prix de vente qui s'établira à la fin de la période. Tous les membres de votre groupe disposent des mêmes informations que vous et devront prendre le même type de décisions. La quantité que vous décidez de produire, sera vendue sur le marché à un prix de vente déterminé uniquement par les décisions de production des 5 autres membres de votre groupe. Tous les membres de votre groupe choisissent les quantités à produire et font leur prévision de prix de vente en même temps.

Au début de l'expérience vous disposez d'un capital de 100 000 points. A chaque période, des points peuvent s'ajouter à ce capital si vous réalisez des gains ou en être retranchés si vous subissez des pertes. A chaque période, le prix de vente sera calculé par l'ordinateur à partir des décisions de production de autres membres de votre groupe. Ce prix vous sera alors communiqué en même temps que votre gain ou perte. Le capital restant (en points) est reporté à la période suivante.

A chaque période vous devez donc prendre deux décisions :

- la quantité que vous voulez produire (un nombre entier compris entre 0 et 900)
- la prévision du prix de vente (un nombre compris entre 0 et 100, ce nombre doit être un multiple de 5)

A chaque période, les informations suivantes vous seront communiquées :

- le prix de vente
- la quantité totale produite par les 5 autres membres de votre groupe
- votre coût de production
- votre gain ou perte lié(e) à la production
- votre gain ou perte lié(e) à la prévision du prix
- votre capital restant pour la période suivante

Avant de démarrer l'expérience, vous prendrez part à deux périodes essai. **Lors de ces deux périodes essai, les décisions des 5 autres membres de votre groupe seront simulées par l'ordinateur.** Ces périodes essai ont uniquement pour but de vous familiariser avec l'environnement de l'expérience. Les points gagnés au cours de ces périodes essai ne seront pas comptabilisés.

A la première période essai, chacun des 5 autres membres simulés de votre groupe va choisir une quantité de 180 unités à produire (donc 900 unités au total produites par les 5 autres membres de votre groupe).

A la deuxième période essai, chacun des 5 autres membres simulés de votre groupe va choisir une quantité de 1 unité à produire (donc 5 unités au total produites par les 5 autres membres de votre groupe) .

Une fois les deux périodes essai terminées, l'ordinateur vous affectera à votre groupe pour les 40 périodes de l'expérience. Le jeu se déroulera avec les autres membres du groupe comme cela a été décrit dans ces instructions. A l'écran, un bouton « Historique » vous permettra d'accéder à l'ensemble des décisions des périodes précédentes.

A la fin des 40 périodes, votre capital final sera converti en euros selon la règle 10 000 points = 1 euro. Ainsi, si votre capital final est par exemple de 200 000 points, vous recevrez 20 euros. Nous vous demandons de remplir alors la feuille de commentaires, et d'attendre à votre place jusqu'à ce qu'un moniteur vienne vous chercher.

Avant de démarrer l'expérience, un questionnaire vérifiera votre bonne compréhension des instructions.

N'hésitez pas à lever la main si vous avez une question !

**Bonne chance !**

- **Unit root tests for price series:**

```
Unit-root tests 2 to 40
Critical values: 5%=-2.938 1%=-3.607; Constant included
fast
                t-adf      beta Y_1    \sigma  lag      AIC
prix1         -5.3748**     0.16379    2.6832   0      2.0239
prix2         -4.9778**     0.27751    3.3600   0      2.4738
prix3         -3.8547**     0.55828    3.3131   0      2.4457
prix4         -8.3597**    -0.20103    1.6021   0      0.9926
prix5         -4.5441**     0.34857    3.7192   0      2.6770
prix6         -4.9778**     0.27751    3.3600   0      2.4738
prix7         -6.3952**    0.061462    2.8829   0      2.1675
prix8         -6.8682**   -0.091703    2.7235   0      2.0538
prix9         -7.1474**   -0.041237    2.8138   0      2.1190
prix10        -4.7944**     0.23362    2.7389   0      2.0651
prix11        -5.2545**     0.45092    1.5106   0      0.8749
prix12        -6.7442**   -0.069444    2.6388   0      1.9906
prix13        -4.2524**     0.34343    3.0128   0      2.2557
prix14        -4.1708**     0.39179    2.7030   0      2.0387
prix15        -6.2046**    0.068182    2.8758   0      2.1625
prix16        -5.3362**     0.21752    3.0207   0      2.2609
```

| | | | | | |
|---|---|---|---|---|---|
| prix17 | -5.3333** | 0.36400 | 2.6148 | 0 | 1.9723 |
| prix18 | -4.3747** | 0.31818 | 2.9844 | 0 | |

***slow***

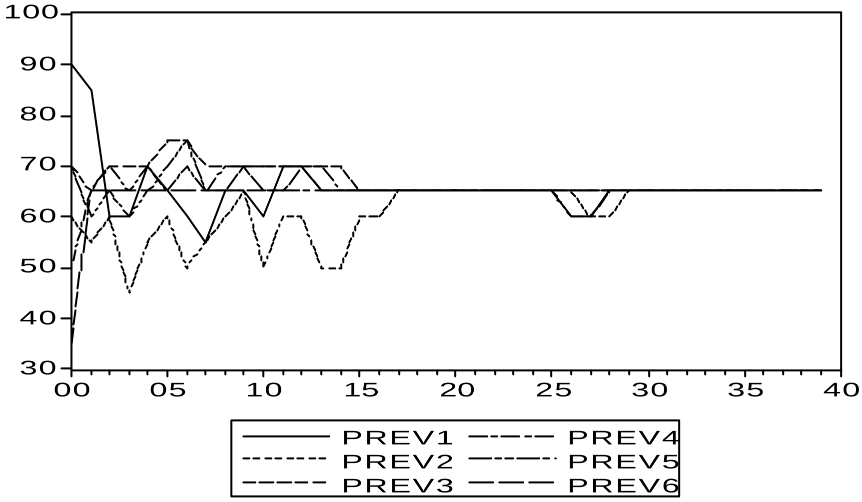
| | t-adf | beta Y_1 | \sigma | lag | AIC |
|---|---|---|---|---|---|
| prix1 | -4.8831** | 0.47561 | 3.9700 | 0 | 2.8075 |
| prix2 | -4.7473** | 0.42966 | 3.9729 | 0 | 2.8089 |
| prix3 | -5.1330** | 0.52232 | 3.3454 | 0 | 2.4651 |
| prix4 | -5.0558** | 0.51074 | 2.7979 | 0 | 2.1077 |
| prix5 | -4.7414** | 0.45155 | 4.0792 | 0 | 2.8617 |
| prix6 | -6.1270** | 0.071429 | 5.1766 | 0 | 3.3382 |
| prix7 | -7.2490** | -0.12353 | 5.8336 | 0 | 3.5772 |
| prix8 | -6.0911** | 0.040603 | 6.4129 | 0 | 3.7665 |
| prix9 | -4.9166** | 0.30196 | 5.6311 | 0 | 3.5065 |
| prix10 | -6.9590** | -0.090909 | 6.1179 | 0 | 3.6723 |
| prix11 | -6.7923** | -0.059915 | 5.4258 | 0 | 3.4322 |
| prix12 | -3.6693** | 0.63420 | 2.8823 | 0 | 2.1671 |
| prix13 | -5.9691** | 0.37556 | 3.5377 | 0 | 2.5769 |
| prix14 | -6.6115** | 0.30000 | 2.7468 | 0 | 2.0708 |
| prix15 | -5.8713** | 0.39567 | 3.2172 | 0 | 2.3869 |
| prix16 | -5.0404** | 0.42745 | 3.5574 | 0 | 2.5880 |
| prix17 | -3.7520** | 0.62240 | 3.6197 | 0 | 2.6227 |
| prix18 | -6.3174** | 0.26874 | 3.6768 | 0 | |

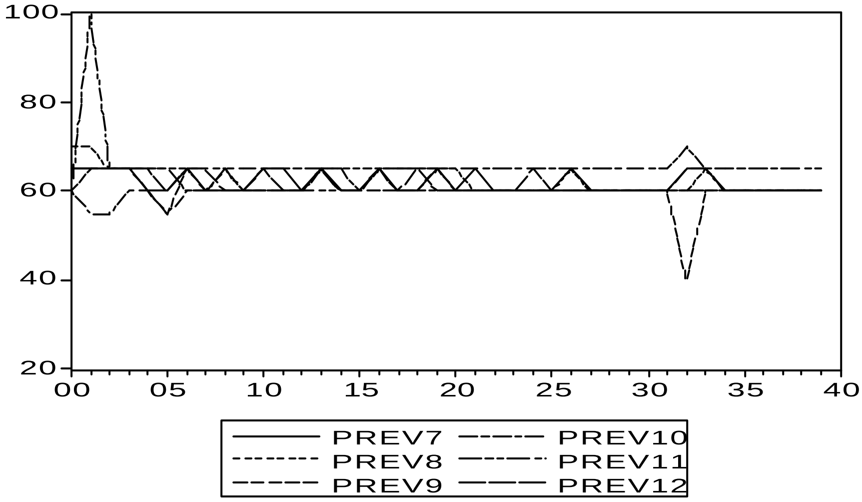
***divergent***

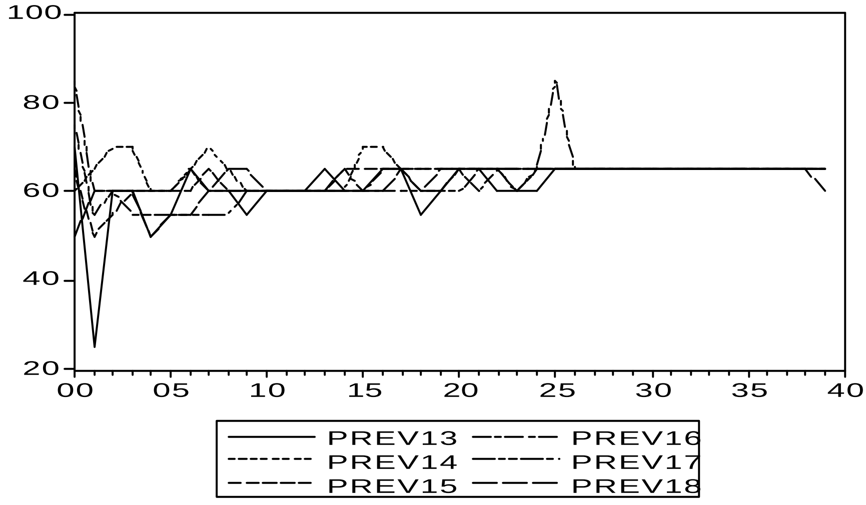
| | t-adf | beta Y_1 | \sigma | lag | AIC |
|---|---|---|---|---|---|
| prix1 | -5.2339** | 0.16907 | 7.6286 | 0 | 4.1137 |
| prix2 | -5.6117** | 0.10945 | 7.3474 | 0 | 4.0386 |
| prix3 | -3.8999** | 0.43888 | 6.3033 | 0 | 3.7321 |
| prix4 | -4.0660** | 0.36901 | 7.8209 | 0 | 4.1635 |
| prix5 | -4.5071** | 0.30512 | 7.6730 | 0 | 4.1253 |
| prix6 | -4.5633** | 0.29525 | 7.7772 | 0 | 4.1523 |
| prix7 | -3.1181* | 0.60512 | 4.7838 | 0 | 3.1804 |
| prix8 | -4.0522** | 0.52582 | 4.5166 | 0 | 3.0654 |
| prix9 | -3.9509** | 0.45529 | 4.5512 | 0 | 3.0807 |
| prix10 | -3.5372* | 0.62793 | 4.7327 | 0 | 3.1589 |
| prix11 | -3.7618** | 0.53047 | 5.4314 | 0 | 3.4343 |
| prix12 | -3.6269** | 0.56048 | 4.7670 | 0 | 3.1734 |
| prix13 | -5.6526** | 0.087222 | 12.497 | 0 | 5.1010 |
| prix14 | -5.8077** | 0.073333 | 11.813 | 0 | 4.9882 |
| prix15 | -4.7141** | 0.39037 | 5.6026 | 0 | 3.4964 |
| prix16 | -6.0160** | 0.042974 | 11.770 | 0 | 4.9810 |
| prix17 | -8.2291** | -0.27174 | 11.763 | 0 | 4.9798 |
| prix18 | -5.1111** | 0.17584 | 13.044 | 0 | 5.1865 |

- **Forecasts:**

***Fast***

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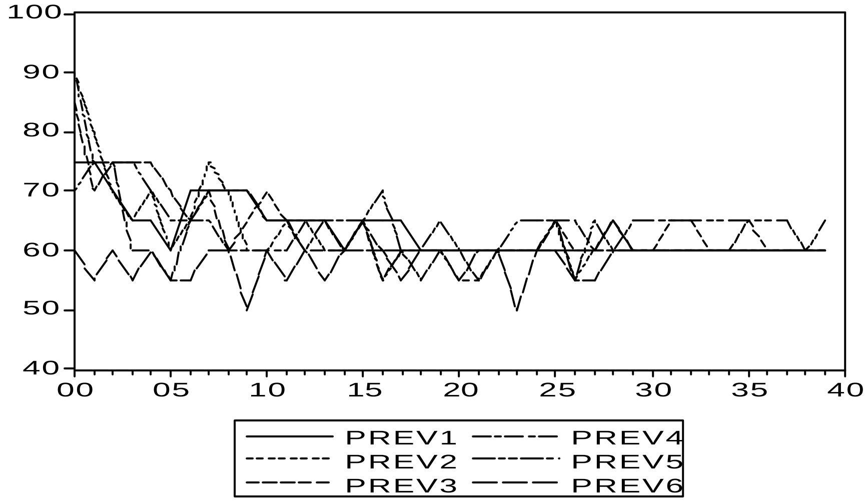
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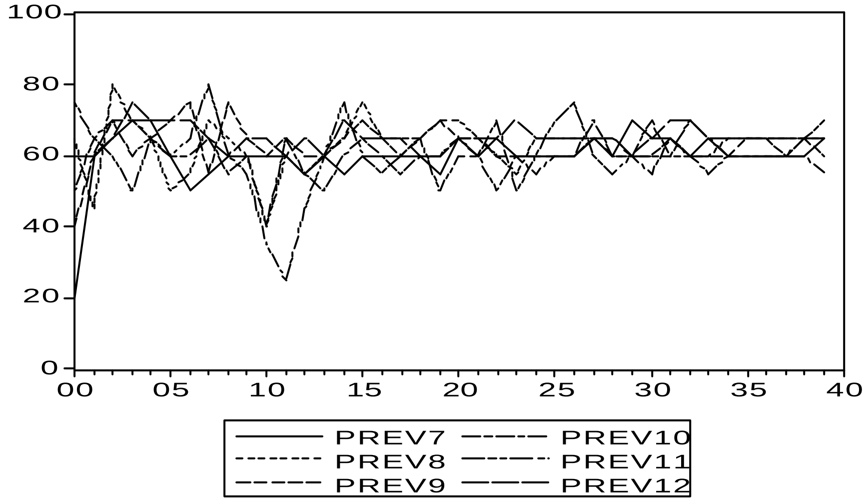
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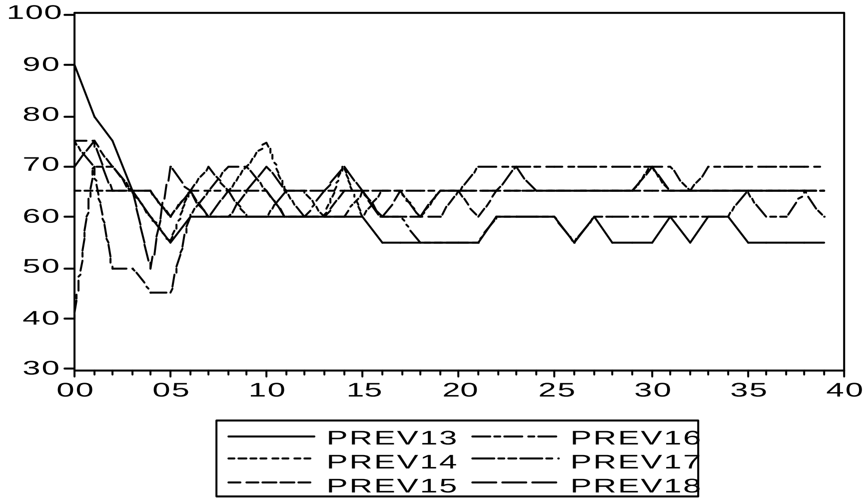
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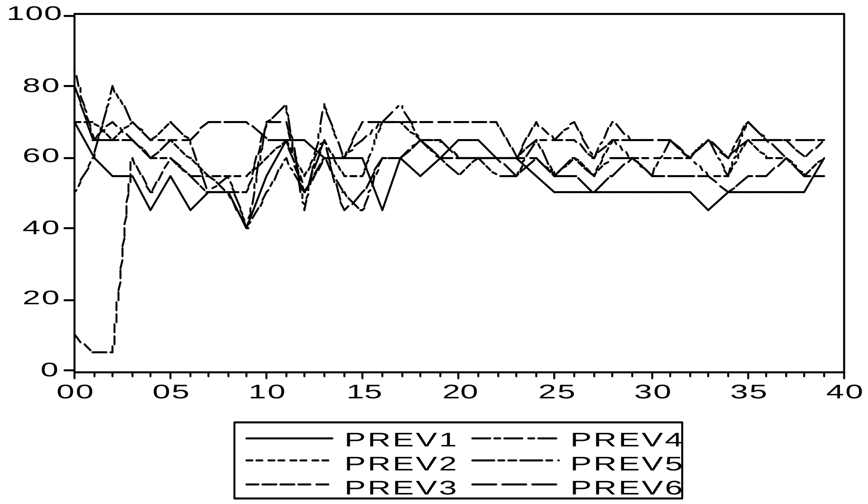
***divergent***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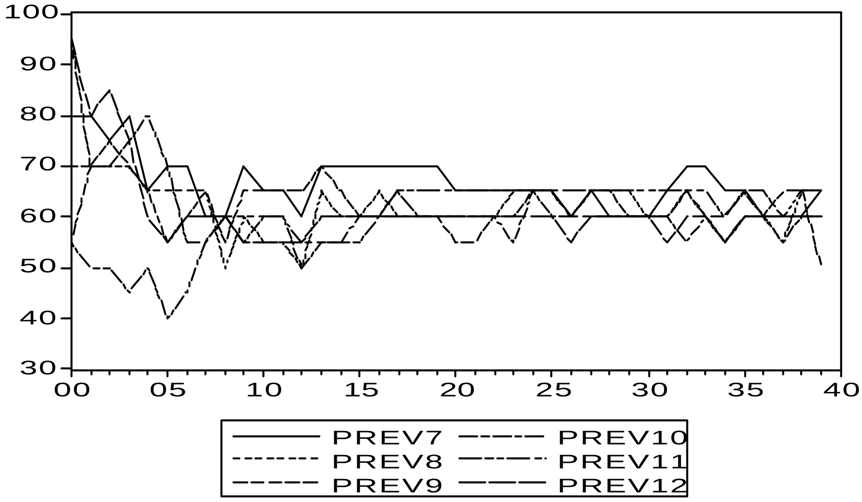
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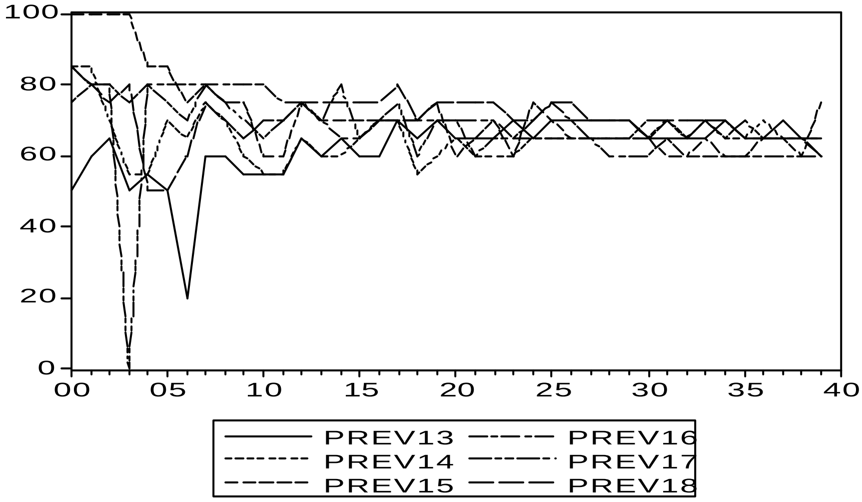
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**Résumé**

Ce travail étudie la mise en place du raisonnement éductif dans des situations de feedback négatif. Nous utilisons une approche expérimentale. Nous construisons cette thèse autour de trois questions : quel est le mécanisme par lequel le raisonnement éductif se met en place ? Existe-t-il des situations dans lesquelles il est plus probable que le raisonnement éductif aboutisse ? Dans ce type de situations, y a-t-il des conditions sous lesquelles les performances de ce type de raisonnement s'améliorent ? Nous identifions les environnements de feedback négatif comme des situations stabilisatrices pour le raisonnement éductif. Ainsi, après avoir défini le concept de raisonnement éductif et caractérisé les environnements de feedback négatif, nous introduisons et testons dans une première partie les jeux du concours de beauté à feedback négatif. La répétition, l'élicitation et la circularité sont des conditions de succès de ce type de raisonnement dans une situation de marché. Ainsi, dans une deuxième partie, nous nous intéressons à l'application des jeux à feedback négatif sur les marchés de type cobweb. Notre thèse montre que, dans des situations de feedback négatif, les croyances réflectives se transforment en croyances intuitives plus rapidement, parce qu'à travers un raisonnement éductif l'équilibre est scanné de manière répétée et l'information utile est accrue. C'est la raison pour laquelle les marchés qui ont une structure de feedback négatif sont stables et les agents qui y interviennent ont des croyances coordonnées.

*Mots clés : raisonnement éductif – feedback négatif – économie expérimentale – jeux du concours de beauté – croyances réflectives – croyances intuitives – modèle cobweb – coordination – anticipations*

**Abstract**

The goal of this thesis is to study the eductive-type of reasoning in negative feedback situations. We address it through an experimental approach. We construct this thesis around three questions: what mechanism is the eductive type of reasoning based on? Is this type of reasoning more likely to succeed in some particular situations? Can we find particular conditions improving the performance of the eductive reasoning? We identify the negative feedback environments as stabilizing situations for the eductive reasoning. Therefore, after defining the concept of eductive reasoning and characterizing negative feedback situations, we introduce and test in the first part of this thesis a negative feedback beauty contest game. Repetition, elicitation and circularity are the conditions of its success within a market situation. Therefore, in the second part of this thesis, we are interested in the application of this game in cobweb markets. Our thesis shows that, in negative feedback situations, reflective beliefs turn faster into intuitive beliefs, because through an eductive type of reasoning, the equilibrium is scanned several times, and useful information is increased. Consequently, a market with a negative feedback structure is stable and the agents within this type of market hold coordinated beliefs.

*Keywords: eductive reasoning – negative feedback – experimental economics – beauty contest games – reflective beliefs – intuitive beliefs – cobweb model – coordination – expectations*