UNIVERSITY OF STRASBOURG

DOCTORAL THESIS

Industry Dynamics, Productivity, Market Power, and Competition: Evidence from French Manufacturing Firms

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Résumé de la Thèse

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Doctorat en Économie

Dynamiques Industrielles, Productivité, Pouvoir de Marché et Concurrence : Une Étude Empirique des Entreprises Manufacturières Françaises

Par

Enrico DE MONTE

Cette thèse étudie différents aspects concernant les dynamiques industrielles, c'est-à-dire l'entrée et la sorties des entreprises, la productivité, la marge économique (le pouvoir de marché), la compétitivité, ainsi que la concurrence entre les entreprises. Des résultats empiriques sont présentés à partir de l'exploitation d'une grande base des données incluant des entreprises actives dans l'industrie manufacturières françaises, pour la période de 1994 à 2016. Après le premier chapitre, faisant office d'introduction générale, le deuxième chapitre étudie la dynamique de productivité agrégée de l'industrie française du bois comme cas particulier de l'ensemble de l'industrie manufacturière française. L'étude est basée sur des données au niveau de l'entreprise de 1994 à 2016, avec pour principaux objectifs d'étudier (i) la croissance de la productivité agrégée tout en tenant compte des entrées et sorties du marché et (ii) la croissance de la productivité agrégée par rapport au statut d'exportation des entreprises et à leur activité économique intérieure et d'exportation. À cette fin, la productivité agrégée est calculée à partir de la productivité au niveau de l'entreprise, qui est estimée sur la base d'une fonction de production à valeur ajoutée à la Cobb-Douglas. Décomposant la contribution à la croissance de la productivité des entreprises en place, entrantes et sortantes, les résultats montrent un ralentissement considérable pendant la crise économique à partir de 2007, principalement induit par une diminution des améliorations de la productivité et une allocation inefficace des ressources entre les entreprises en place. De plus, l'étude montre que les exportateurs contribuent davantage à la croissance de la productivité globale que les non-exportateurs. En examinant la contribution des activités

économiques nationales et d'exportation des entreprises à la croissance de la productivité globale, les résultats montrent que la croissance de la productivité globale est principalement liée à l'activité économique domestique des entreprises.

Le troisième chapitre généralise l'analyse du chapitre précédent à la fois méthodiquement et en considérant l'ensemble de l'industrie manufacturière française. Le chapitre examine l'évolution de la productivité agrégée et des marges économiques agrégées des entreprises manufacturières françaises entre 1994 et 2016, en tenant compte les entrées et sorties de marché. La productivité et les marges au niveau de l'entreprise sont estimées sur la base d'une fonction de production translog. L'effet de l'entrée et de la sortie d'entreprises sur la productivité agrégée et les marges économiques est analysé en appliquant une méthode de décomposition appropriée. Les résultats montrent une croissance de la productivité agrégée d'environ 48 % sur l'ensemble de la période, qui est principalement due aux gains de productivité des entreprises en place. Cependant, les résultats suggèrent que la croissance de la productivité s'est ralentie à partir de 2000, induite par un processus de redistribution plus lent des parts de production entre les entreprises en place. Les marges bénéficiaires agrégées restent relativement stables au fil du temps, avec les entreprises en place qui ont une contribution clairement positive aux marges bénéficiaires globales, tandis que les effets des entrées et des sorties d'entreprises sur l'évolution de la marge agrégée varient dans le temps. Une analyse des différences de marges sur la base d'un cadre de régression révèle que les entrants appliquent des marges plus faibles, même lorsqu'ils contrôlent la technologie, ce qui suggère que ces entreprises ont beaucoup moins de pouvoir de marché et / ou adoptent une politique de prix agressive afin de s'imposer sur le marché.

Le quatrième chapitre modélise explicitement la concurrence à la Cournot entre les, où les entreprises choisissent de manière optimale leur quantité de production, compte tenu de leur technologie ainsi que le comportement de leurs concurrents. Le modèle repose sur deux composantes: premièrement, le mécanisme des prix, où les entreprises sont censées être preneuses de prix, face à un prix commun, et deuxièmement, la technologie des entreprises, qui est décrite par leur fonction de coût individuelle. Ce chapitre caractérise l'équilibre de Cournot à court et à long terme avec des entreprises hétérogènes ainsi que le changement technologique stochastique. On considère ici les entreprises avec des technologies différentes, c'est-à-dire avec des coûts fixes et variables hétérogènes et des divers degrés de pouvoir de marché sur le marché des produits. Le chapitre étend les modèles existants avec des entreprises homogènes au cas des entreprises hétérogènes et montre qu'une concentration industrielle plus élevée de la production améliore le bien-être. Empiriquement, en utilisant les données des entreprises manufacturières en France, on constate une grande hétérogénéité des technologies, où les paramètres technologiques sont identifiés qui permettent de mieux reproduiser la répartition observée de la taille des entreprises.

Le cinquième chapitre est lié au chapitre précédent, puisqu'il considère l'estimation économétrique de la fonction de demande inverse. En particulier, le chapitre développe un estimateur instrumental nonparamétrique en contrôlant les effets fixes non observés. Dans le cas de la fonction de demande inverse, la vraie relation entre les prix et la production est inconnue et, par conséquent, l'estimation nonparamétrique est prometteuse pour éviter les erreurs de spécification dans la forme fonctionnelle du modèle de demande inverse. Ici, la variable dépendante, c'est-à-dire le niveau des prix, est probablement affectée par des chocs macroéconomiques et spécifiques à l'industrie. Ces chocs étant difficiles à modéliser et susceptibles d'être corrélés à la variable explicative, c'est-à-dire le niveau de production, sont généralement pris en compte par des effets fixes non observés. De plus, ici les variables dépendante et explicative pourraient être déterminées conjointement par le mécanisme d'équilibre de l'offre et e la demande, conduisant à un biais de simultanéité. Dans un tel cas, les techniques de régression à variable instrumentale (IV) et à effets fixes (FE) doivent être appliquées pour faire face aux diverses sources d'endogénéité. Pour les modèles paramétriques et en particulier linéaires, cela représente une stratégie commune d'estimation et d'identification. S'appuyant sur les méthodes existantes de régression nonparamétriques, le chapitre cherche à fournir une solution nonparamétrique facilement applicable pour différents types de modèles de panel endogènes, c'est-à-dire avec des effets individuels, temporels, ou les deux simultanément. Les résultats des simulations suggèrent une bonne performance à taille limitée de l'échantillon de l'estimateur nonparametrique proposé. De plus, l'estimateur est appliqué sur des données agrégées des industries manufacturières américaines. Les résultats montrent que la quantité n'est pas toujours décroissante dans les prix, ce qui suggère la mal spécification des modèles paramétriques utilisés dans la littérature et implique également une violation de la loi de demande.

Enfin, le sixième chapitre résume la thèse et discute les limites et les extensions possibles.

Abstract of thesis entitled

Industry Dynamics, Productivity, Market Power, and Competition: Evidence from French Manufacturing Firms

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Enrico De Monte

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This thesis examines various aspects related to industry dynamics, i.e. firm entry and exit, productivity, markups, and competition among firms. Empirical evidence is brought by the exploitation of a large panel dataset, including firms active in the French manufacturing industry for the period from 1994 to 2016.

Followed by first chapter, the general introduction, the second chapter investigates aggregate productivity dynamics of the French woodworking industry as as special case of the overall French manufacturing. The study is based on firm-level data from 1994 to 2016 with the main objectives to investigate (i) aggregate productivity growth while taking market entry and exit into account and (ii) aggregate productivity growth with respect to firms' export status and with respect to their domestic and export economic activity. For that purpose, aggregate productivity is derived from firm-level productivity, which is estimated based on a value-added production function. Decomposing the productivity growth into the contribution of incumbent, entering, and exiting firms, the results show a considerable slowdown during the economic crisis from 2007 on, which is mainly induced by decreasing productivity improvements and inefficient resource allocation among incumbent firms. Moreover, the study shows that exporters contribute more to aggregate productivity growth than non-exporters. Investigating the contribution of firms' domestic and export economic activities on aggregate productivity growth, the findings show that aggregate productivity growth is mainly related to firms' domestic economic activity.

The third chapter generalizes the analysis of the previous chapter both methodically and by considering the entire French manufacturing industry. The chapter investigates the development of aggregate productivity and aggregate markups among French manufacturing firms between 1994 and 2016, taking market entry and exit into account. Firm-level productivity and markups are estimated based on a gross output translog production function.

The effect of firm entry and exit on aggregate productivity and markups is analysed by applying an appropriate decomposition method. The findings show an aggregate productivity growth of about 48% over the whole period, which is mainly driven by productivity gains among incumbent firms. However, the results suggest that productivity growth has slowed down from 2000 on, induced by a slower reallocation process of output shares among incumbent firms. Aggregate markups are found to remain relatively stable over time, with incumbent firms having a clearly positive contribution to aggregate markups, whereas the effects of firm entries and firm exits on aggregate markups vary over time. An analysis of markup differences based on a regression framework reveals that entrants apply lower markups even when controlling for technology, which suggests that these firms have considerably less market power and/or adopt an aggressive price policy in order to prevail in the market.

The fourth chapter explicitly models competition among firms à la Cournot, where firms optimally chose their output quantity, given their cost efficiency and the choices of their competitors. The model is built on two components: first, the price mechanism, where firms are supposed to be price-takers, facing a common price, and second, by firms' technology, which is described by their individual cost function. In this chapter the short and long-run Cournot equilibrium with heterogeneous firms is characterized, along with stochastic technological change. Here firms with different technologies, i.e., with heterogeneous fixed and variable costs and various degrees of market power in the product market are considered. The chapter extends existing models with homogenous firms to the case of heterogeneous firms and shows that higher industrial concentration of production is welfare improving. Using data for manufacturing firms in France, the empirical results highlight the importance of both observed and unobserved heterogeneity for explaining firms' cost and marginal revenues. Fixed costs are often very small, but found to be significant for the smallest and largest firm sizes, which may have policy implications, both for increasing the survival probability of small firms, than for fighting inefficiencies (or market power) of bigger firms.

The fifth chapter is closely related to the previous chapter by considering the econometric estimation of the inverse demand function. In particular, the chapter develops a nonparametric instrumental estimator by controlling for unobserved fixed effects. In the case of the inverse demand function, the true relation between prices and output is unknown and, thus, nonparametric estimation is promising to avoid missspecifcation in the functional form of the inverse demand model. Here, the dependent variable, i.e. the price level, might be shifted by macroeconomic and industry specific shocks. Since these shocks are difficult to model and likely to be correlated with the explanatory variable, i.e. the production level, they are usually taken into account by unobserved fixed effects. Moreover, here de dependent and the explanatory variable might be jointly determined by the equilibrium mechanism, leading to simultaneity bias when not taken into account. In such a case both instrumental variable (IV) and fixed effects (FE) regression techniques should be applied to cope with the various sources of endogeneity. For parametric and especially linear models this is a common estimation and identification strategy. Building on existing nonparametric kernel regression methods, the chapter seeks to provide an easily applicable nonparametric solution for different kinds of endogenous panel models, i.e. with individual, time or two-ways effects. The simulation results suggest good finite sample behavior of the proposed estimator. The estimator is also applied to estimate the inverse demand function, based on price and output data of U.S. manufacturing industries.

Finally, the sixth chapter summarizes the thesis and discusses limitation and extentions.

Industry Dynamics, Productivity, Market Power, and Competition: Evidence from French Manufacturing Firms

by **Enrico DE MONTE**

A Thesis Submitted in Partial Fulfilment
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Declaration

I, Enrico DE MONTE, declare that this thesis titled, "Industry Dynamics, Productivity, Market Power, and Competition: Evidence from French Manufacturing Firms", which is submitted in fulfillment of the requirements for the Degree of Doctor of Philosophy, represents my own work except where due acknowledgement have been made. I further declared that it has not been previously included in a thesis, dissertation, or report submitted to this University or to any other institution for a degree, diploma or other qualifications.

Date: June 3, 2021

I dedicate this thesis to my beloved parents, Roswita and Pierluigi, as well as to my dear brother Daniel, for their unconditional love and support.

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Enrico De Monte
University of Strasbourg
June 3, 2021

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List of Abbreviations

ACF	**A**ckerberg-**Caves**-**F**racer
AGR	**A**verage **G**rowth **R**ate
CD	**C**obb- **D**ouglas
CES	**C**onstant **E**lasticity of **S**ubstitution
DGP	**D**ata **G**enerating **P**rocess
DOPD	**D**ynamic **O**lley-**P**akes **D**ecomposition
FARE	**F**ichier **A**pproché des **R**ésultats d'**E**sane
FD	**F**irst **D**ifference
FE	**F**ixed **E**ffects
FOC	**F**irst-**O**rder **C**onditions
FICUS	**F**ichier de **C**omptabilité **U**nifié dans **S**USE
GDP	**G**ross **D**omestic **P**roduct
GMM	**G**eneralized **M**ethods of **M**oments
LMU	**L**ee-**M**ukherjee-**U**llah
L-F	**L**andweber-**F**ridman
LL	**L**ocal-**L**inear
LP	**L**evinsohn-**P**etrin
LRCE	**L**ong-**R**un **C**ournot **E**quilibrium
LRWP	**L**ong-**R**un **W**elfare maximizing**P**oint
MAD	**M**edian **A**bsolute **D**eviation
IO	**I**dustrial **O**rganisation
IV	**I**strumental **V**ariable
NAF	**N**omenclature d'**A**ctivités **F**rançaises
OLS	**O**rdinary **L**east **S**quares
OP	**O**lley-**P**akes
RTC	**R**ate of **T**echnological **C**hange
RTS	**R**iturns **T**o **S**cale
TL	**T**rans**l**og
w.r.t.	**w**ith **r**espect **t**o

Chapter 1

Introduction générale

1.1 Motivation

Les dynamiques industrielles peuvent être décrites comme un processus continu de renouvellement d'une industrie. Les entreprises entrent, grandissent, rétrécissent et peuvent finalement quitter le marché, où chaque entreprise individuelle façonne l'industrie avec son activité. Il existe diverses mesures qui décrivent l'évolution d'une industrie : le nombre d'entreprises actives, la répartition de la taille des entreprises, le montant de la production totale, l'emploi total, et bien d'autres. Une manière appropriée d'illustrer la dynamique de l'industrie consiste à considérer les industries émergentes, pour lesquelles certaines régularités ont été observées. Par exemple, les industries émergentes se caractérisent par un taux élevé d'entrée d'entreprises au début, ce qui entraîne une forte augmentation du nombre d'entreprises actives. A partir d'un certain niveau de développement de l'industrie, le nombre d'entreprises diminue. La littérature appelle ce phénomène le "shakeout". Le niveau total de production de l'industrie est plus élevé, avec moins d'entreprises présentes sur le marché (Smith, 1968; Gort and Klepper, 1982; Klepper and Graddy, 1990; Jovanovic and MacDonald, 1994). Une rentabilité insuffisante, c'est-à-dire des coûts d'exploitation supérieurs aux revenus, est la raison la plus importante pour laquelle les entreprises cessent leurs activités. La rentabilité d'une entreprise, quant à elle, est fortement déterminée par sa productivité, qui est affectée par l'innovation dans la technologie de production (R&D), la qualité des facteurs de production, ainsi que l'apprentissage par la pratique (Syverson, 2011). Par conséquent, les entreprises peu productives sont susceptibles de cesser leur activité à long terme, et d'être remplacées par des entreprises en place ou par les nouvelles entrantes, plus productives. Schumpeter (1942) appelle ces dynamiques le processus de la destruction créative.

Pour une meilleure compréhension du concept de productivité et de son importance, prenons l'exemple du niveau de production, au niveau de l'entreprise ou de l'industrie. Le niveau de production augmente (i) soit en utilisant plus de facteurs de production (capital, travail et / ou matériaux) (ii) soit en augmentant l'efficacité avec laquelle ces facteurs sont transformés en production. Ce dernier mécanisme, qui saisit les changements de la production qui ne peuvent pas être expliqués par les changements des facteurs de production, est généralement appelé productivité totale des facteurs. De nombreuses études ont montré que les différences de niveau de production entre les pays peuvent en grande partie être expliquées par des différences de productivités agrégées (Mankiw et al., 1992; Prescott, 1998; Hall and Jones, 1999). De plus, l'augmentation de productivité a des effets importants sur la croissance et la prospérité à long terme d'une économie (Caselli, 2005). En effet, la productivité est liée au processus d'apprentissage et à l'activité innovante des entreprises, ce qui est essentiel, sinon indispensable, pour une croissance durable, tant au niveau micro (entreprise) qu'au niveau macro (industrie ou pays). En outre, du point de vue du bien-être économique, dans un environnement concurrentiel, un niveau plus élevé de productivité globale réduit les coûts et, par conséquent, le surplus des producteurs et des consommateurs augmente.

La productivité est donc largement considérée comme un facteur crucial pour comprendre le fonctionnement et la performance d'une industrie. À ce titre, il jouera un rôle clé dans cette thèse pour étudier la dynamique de l'industrie manufacturière française. Cependant, la productivité n'est pas une variable observable, mais généralement un facteur non observé dans le processus de production. Cerner ce facteur non observé est un sujet de recherche important dans le domaine de l'économie industrielle et plus particulièrement dans la théorie du producteur, où le processus de production d'une entreprise est représenté par une fonction de production qui transforme les facteurs de production ainsi que la productivité non observée en quantité de production. La productivité au niveau de l'entreprise est ensuite calculée sur la base de l'estimation de la fonction de production de l'entreprise. Cette approche, qui est aujourd'hui la méthodologie établie pour estimer la productivité, sera également suivie ici. Pour cette raison, la méthodologie appliquée pour estimer la productivité au niveau de l'entreprise est basé sur l'estimation des fonctions de production.

L'utilisation des fonctions de production pour étudier le comportement de production des entreprises a une longue tradition dans le domaine de l'économie industrielle et remonte à Cobb and Douglas (1928) qui a fourni la première expression formelle d'une fonction de production. D'autres chercheurs ont suivi comme, Frisch (1935) qui a étudié la substituabilité entre les facteurs de production et Arrow et al. (1961) qui a développé ce que la littérature réfère à la fonction de production CES (Constant Elasticity of Substitution) . Samuelson (1963) et Shephard (1970) ont présenté le concept de dualité de production qui montre le lien entre la maximisation de la production et la minimisation des coûts des entreprises. Pour les études empiriques, la fonction de production à la Cobb-Douglas ainsi que la fonction de production CES impliquent des restrictions paramétriques importantes. Motivés par ces contraintes, les travaux fondateurs de Diewert (1971) et Christensen et al. (1971) ont fourni des spécifications des fonctions de production plus flexibles. Les recherches à ce sujet sont toujours en train de se développer, par exemple, Gandhi et al. (2020) et Demirer (2020) développent des approches non-paramétriques pour réduire, encore plus, les restrictions dans les paramètres.

Une fois que la productivité au niveau de l'entreprise est estimée de manière convergente, elle peut être agrégée pour étudier la performance d'une économie donnée en termes de trajectoire de productivité. Dans la littérature, une mesure largement utilisée de la productivité agrégée est la moyenne pondérée, où la productivité des entreprises est pondérée par leurs parts de production (Olley and Pakes, 1996; Van Biesebroeck, 2008). Sur la base de cette approche, la productivité agrégée peut augmenter pour deux raisons : (i) si les entreprises augmentent leur niveau individuel de productivité et (ii) si les pondérations, c'est-à-dire les parts de production, passent des entreprises moins productives aux entreprises plus productives. (i) est appelé changement de productivité intra-entreprise par l'apprentissage et (ii) est appelé changement inter-entreprise, également connu sous le nom de processus de réallocation des ressources. L'efficacité d'allocation, en général, a beaucoup retenu l'attention dans ce domaine, où la question fondamentale est de savoir par quelle allocation des ressources une économie atteint le plus haut niveau de productivité agrégée. Si, par exemple, les facteurs de production sont alloués aux entreprises avec une productivité marginale des facteurs (de production) plus petits, les ressources sont moins efficacement utilisées et, par conséquent, la productivité globale est plus faible (Restuccia and Rogerson, 2008, 2013; Hsieh and Klenow, 2009) Haltiwanger (2011) décrit qu'une économie "fonctionne bien" si l'économie présente deux caractéristiques. Premièrement, l'efficacité allocative statique, c'est-à-dire si les entreprises plus productives produisent plus par rapport aux entreprises moins productives. Deuxièmement, l'efficacité allocative dynamique, c'est-à-dire si les parts de production passent progressivement d'entreprises peu productives à des entreprises plus productives. Dans cette thèse, l'utilisation d'une méthode appropriée de décomposition de la productivité agrégée permet de mesurer les différents effets liés à l'apprentissage des entreprises, à la réallocation des ressources et aux entrées et sorties d'entreprises sur la croissance de la productivité agrégée.

Dans ce contexte, la thèse étudie également l'évolution du pouvoir de marché des entreprises. En général, le pouvoir de marché décrit la capacité d'une entreprise à fixer des prix au-dessus de ses coûts marginaux - un écart également connu sous le nom de marge bénéficiaire. Étant donné que les prix de la production et les coûts marginaux ne sont généralement pas observés, les marges doivent être estimées économétriquement, ce qui permet de conjecturer sur le pouvoir de marché des entreprises. Dans ce but, Hall (1986, 1988) a développé un approche économétrique pour estimer les marges (moyennes) au niveau des industries. Cette approche se base sur l'estimation d'une fonction de production, ce qui souligne leur utilité concernant les études empiriques. En s'appuyant sur ces travaux De Loecker (2011) et De Loecker and Warzynski (2012) fournissent des méthodologies pour estimer les marges au niveau de l'entreprise individuelle. Récemment, il y a eu une discussion animée sur la question de savoir s'il y a une augmentation systématique du pouvoir de marché (Hall, 2018; Traina, 2018; De Loecker et al., 2018; Autor et al., 2020; De Loecker et al., 2020; Demirer, 2020). C'est une question très importante car les changements de pouvoir de marché ont des implications sur les tendances séculaires de l'économie. Par exemple, un niveau de pouvoir de marché plus élevé est associé à un taux d'entrée plus faibles, à moins d'investissements en capital et, par conséquent, à moins d'innovation, ce qui entrave les améliorations de la productivité. Il est également démontré que la hausse des marges explique la diminution de la part du travail, qui est motivée par le comportement de minimisation des coûts des entreprises, où des marges plus élevées réduisent directement la demande de main-d'œuvre et d'investissement en capital des entreprises. En conséquence, il est démontré que l'augmentation des marges réduit considérablement le bien-être (Edmond et al., 2018; Berry et al., 2019; Syverson, 2019; De Loecker et al., 2020).

Enfin, cette thèse étudie explicitement l'efficacité dans les coûts des entreprises ainsi que le bien-être économique via un modèle structurel de concurrence. Le modèle intègre diverses caractéristiques clés de l'industrie et de l'entreprise, telles que le comportement stratégique des entreprises, l'hétérogénéité de la technologie de production et le pouvoir de marché. Comme mentionné brièvement, dans un environnement concurrentiel, les entreprises sont incitées à accroître leur niveau d'efficacité. Autrement dit, un niveau d'efficacité inférieur est lié à des coûts de production plus élevés, ce qui, à son tour, oblige l'entreprise à fixer des prix de production plus élevés. En conséquence, par rapport à des concurrents plus efficaces, les entreprises inefficaces choisissent elles-mêmes de quitter le marché à long terme. Il existe différents modèles d'équilibre du marché dans la littérature qui visent à représenter la concurrence des entreprises et le processus de sélection du marché (Jovanovic, 1982; Hopenhayn, 1992; Ericson and Pakes, 1995). Dans cette thèse, le modèle de concurrence bien connu de Cournot est étudié, dans lequel les entreprises sont supposées faire des choix optimaux par rapport à leur quantité de production, en tenant compte de leur technologie ainsi que des choix de production de leurs concurrents (Amir, 1996; Amir and Lambson, 2000; Götz, 2005; Ledezma, 2021). Ici, la technologie des entreprises est représentée par leur fonction de coût, celle-ci traduit les prix des facteurs de production, la quantité de production et l'efficacité dans les coûts non observés (hétérogènes) en coûts totaux. L'analyse du modèle donne de nouvelles bases microéconomiques du comportement stratégique des entreprises dans un environnement concurrentiel et permet la caractérisation théorique et empirique d'entreprises inefficaces et efficientes. Il est important de noter que le modèle est également utilisé pour étudier les effets sur le bien-être économique. Autrement dit, du point de vue d'un planificateur social, la question relève de la manière dont la production des entreprises individuelles doit être allouée pour minimiser les coûts globaux, soit en d'autres termes, pour maximiser le bien-être économique global.

1.2 Sommaire de la thèse

Cette thèse contribue à la littérature par une analyse détaillée des sujets mentionnés, c'est-à-dire, l'évolution de la productivité et du pouvoir de marché agrégé, l'allocation des ressources, l'entrée et la sortie d'entreprises et l'efficacité des entreprises dans un environnement concurrentiel. Les résultats empiriques sont issus du traitement des données individuelles d'entreprise. En particulier, le traitement des bases de données FICUS, de 1994 à 2007, et FARE, de 2008 à 2016. FICUS et FARE font référence au "fichier de comptabilité unifié dans SUSE" et au "fichier approché des résultats d'Esane", respectivement. FICUS faisait partie de la base de données des entreprises de SUSE, qui a été remplacée en 2008 par FARE, qui actuellement fait partie de la base de données d'Esane. FICUS et FARE sont des bases de données fiscales, construites grâce à l'obligation des entreprises de rapporter les informations contenant dans le bilan et dans le compte de résultat. Par la suite, un court sommaire des chapitres de la thèse est présenté. Plus bas, un sommaire plus détaillé de chaque chapitre est fourni.

- Chapitre 2 analyse les dynamiques de productivité agrégée de l'industrie des produits forêt-bois, prenant en compte l'entrée et la sortie des entreprises. De plus, les dynamiques de productivité agrégée sont liées au comportement d'exportation des entreprises.
- Chapitre 3 considère l'ensemble de l'industrie manufacturière et étudie l'évolution de la productivité agrégée ainsi que le pouvoir de marché des entreprises en prenant en compte l'entrée et la sortie des entreprises.
- Chapitre 4 analyse la situation de concurrence à la Cournot ainsi que le bien-être économique, où l'hétérogénéité est introduit à travers les coûts fixes et variables. Le modèle est estimé économétriquement en utilisant les données des entreprises manufacturières françaises.
- Chapitre 5 développe un estimateur instrumental nonparamétrique avec des effets fixes - un exercice demandé lorsqu'on souhaite, par exemple, estimer la fonction de demande inverse présente dans le modèle de Cournot. L'estimateur est testé à la base des données simulées ainsi qu'appliqué à des données agrégées des industries manufacturières des États Unis.

1.2.1 Chapitre 2: Les dynamiques de productivité et le rôle des exportations de l'industrie des produits forêt-bois française

Le deuxième chapitre considère l'industrie des produits forêt-bois comme un cas particulier de l'industrie manufacturière française. Plus précisément, la croissance de la productivité agrégée y est étudiée en prenant en compte l'entrée et la sortie des entreprises du marché. Ici, la productivité au niveau des entreprises est estimée à la base d'une fonction de production à la Cobb-Douglas (Ackerberg et al., 2015). Par la suite, une méthode de composition est appliquée pour analyser la contribution à la productivité agrégée des entreprises qui survivent dans le marché, ainsi que la contribution des entreprises qui entrent et qui sortent du marché (Melitz and Polanec, 2015). Dans une deuxième partie, la productivité agrégée est liée au comportement d'exportation des entreprises, plus précisément à leur statut d'exportation (les entreprises exportatrices ou non-exportatrices) et par rapport à l'intensité d'exportation (le volume de production vendu sur le marché domestique et étranger). L'analyse de l'industrie des produit forêt-bois en particulier est motivée par le fait qu'elle est devenue une industrie clé pour affronter des problématiques actuelles et futures par rapport au changement climatique et à la transition énergétique, c'est-à-dire la réduction des émissions de CO_2 ainsi que la plus grande demande de ressources durables (Lundmark, 2010). Notamment en 2013 le gouvernement français a inclus, entre autres, l'industrie des produits forêt-bois domestique dans le plan d'action public intitulé *"La Nouvelle France Industrielle"*, avec l'objectif d'affronter ces défis à une plus grande échelle. Par conséquent, une grande importance est attribuée à l'industrie des produits forêt-bois, ce qui demande une compréhension plus profonde de sa performance et sa soutenabilité économique. L'analyse de la relation entre la productivité agrégée et le comportement d'exportation des entreprises est motivée par le fait que la balance commerciale de l'industrie française des produits forêt-bois montre une tendance négative sur les dernières années, représentant approximativement 10% du déficit commercial français total (Levet et al., 2014). Généralement, la taille de la superficie forestière d'un pays est un facteur de compétitivité important au regard de l'avantage comparatif concernant le commerce des produits forêt-bois (Lundmark, 2010; Levet et al., 2015; Koebel et al., 2016). Or, malgré que la France soit un des pays avec le plus de régions forestières, l'industrie forêt-bois française ne semble pas en mesure d'exploiter cet avantage, en témoigne son déficit commercial important dans ce secteur.

Les résultats suggèrent que la productivité agrégée de l'industrie des produits forêt-bois a augmenté considérablement pendant les périodes 1994-2000 et 2001-2007. Pendant la période de crise économique, 2008-2012, la croissance de la productivité agrégée a ralentie d'une manière importante. Ensuite, de 2012-2016, la croissance de la productivité agrégée repart à la hausse. Le facteur le plus important pour ces dynamiques est la contribution du groupe des entreprises qui survivent au cours des différentes périodes. De plus, l'analyse de la croissance de la productivité agrégée par rapport au statut d'exportation des entreprises montre que la productivité agrégée des entreprises qui exportent croit plus durablement durant les différentes périodes étudiées comparativement aux entreprises qui n'exportent pas. Cependant, les résultats montrent aussi que l'activité économique domestique contribue bien plus à la croissance de la productivité agrégée que l'activité d'exportation, ce qui est dû au fait que les entreprises distribuent la plus grande partie de leur production sur le marché domestique. Ces résultats laissent donc entendre qu'une orientation plus forte vers le marché international, à la fois en termes de nombre d'entreprises qui exportent et en termes des volumes exportés, pourrait amener une croissance de la productivité plus importante et durable.

1.2.2 Chapitre 3: Productivité, marge économique, entrée et sortie : Une étude empirique des entreprises manufacturières françaises

Le troisième chapitre élargit l'analyse à l'ensemble de l'industrie manufacturière française. En plus de l'évolution de la productivité agrégée, ce chapitre étudie également l'évolution de la marge économique agrégée des entreprises, toujours en prenant en compte l'entrée et la sortie des entreprises (Melitz and Polanec, 2015). Une généralisation supplémentaire par rapport au premier chapitre est faite en estimant la productivité au niveau individuel des entreprises à l'aide d'une fonction de production translog, à partir de laquelle la marge économique est calculée (Ackerberg et al., 2015; De Loecker and Warzynski, 2012). Récemment, les discussions autour du niveau et de l'évolution des marges économiques - décrivant le pouvoir de l'entreprise de demander un prix au-dessus du coût marginal de production - a repris de l'ampleur. Par exemple, en analysant l'économie américaine entre 1960 et 2016, De Loecker et al. (2020) montre dans une étude de grande ampleur une augmentation importante de la marge agrégée à partir de 1980. Contrairement à la productivité, un niveau plus important de la marge, c'est-à-dire un niveau de pouvoir de marché des entreprises plus important, est associé à un taux d'entrée des entreprises plus faible, moins d'investissement dans le capital et finalement moins d'innovations (De Loecker et al., 2020; Edmond et al., 2018).

Les résultats montrent que le niveau de productivité agrégée de l'industrie manufacturière française a augmenté d'environ 48% entre 1994 et 2016. Cette croissance a été possible principalement par l'amélioration de la productivité des entreprises établies (survivantes) et bien moins par les dynamiques d'entrées et sorties des entreprises. D'autres études sur l'économie française confirment un ralentissement de la croissance de la productivité agrégée depuis l'année 2000 (Cette et al., 2017; Ben Hassine, 2019). De plus, la marge économique agrégée varie pendant la période 1994-2016. Les résultats ne confirment donc pas une augmentation systématique comme documenté pour l'économie américaine (De Loecker et al., 2020). Les entreprises établies maintiennent un niveau de marge considérablement plus important et contribuent positivement à la marge agrégées. L'effet net de l'entrée et de la sortie des entreprises montre que ce sont particulièrement les nouvelles entreprises qui entrent dans le marché qui contribuent négativement à l'évolution de la margé agrégée. Finalement, une analyse plus fine pour mieux comprendre la relation entre la marge et des différentes caractéristiques des entreprises est menée à partir d'un modèle de régression.

Les résultats suggèrent que les entrants maintiennent un pouvoir de marché inférieur et/ou demandent des prix inférieurs pour s'assurer de se maintenir dans le marché.

1.2.3 Chapitre 4: L'équilibre du modèle de Cournot avec des entreprises hétérogènes

Le quatrième chapitre modélise explicitement la situation de concurrence à la Cournot, où les entreprises sont supposées choisir le niveau de production de manière optimale - étant donnée leur technologie (en terme d'efficacité dans leur coût de production) et en prenant en compte le choix optimal de leur concurrents. Le modèle est basé sur deux composantes principales : (i) le mécanisme des prix, selon lequel les entreprises sont supposées accepter un prix commun qui est déterminé par le niveau de production agrégé - un mécanisme qui est formellement décrit par la fonction de demande inverse ; (ii) la technologie des entreprises qui est décrite par la fonction de coût spécifique à chaque entreprise.

Dans une première partie théorique, le chapitre caractérise l'équilibre de Cournot de court et de long terme avec des entreprises hétérogènes dont la technologie suit un mouvement stochastique. Ici, les différences de technologies sont modélisées à travers l'hétérogénéité dans le coût fixe et le coût variable. Dans un cadre avec des entreprises homogènes, Mankiw and Whinston (1986) a montré que l'équilibre de Cournot de long terme peut être inefficace à cause d'un taux d'entrée des entreprises trop élevé. Ce chapitre élargit ce résultat théorique pour le cas des entreprises hétérogènes et montre qu'une concentration de production industrielle plus importante augmente le bien-être économique. Une deuxième partie du chapitre introduit la méthode économétrique pour estimer le modèle, notamment la fonction de demande inverse et la fonction de coût. Utilisant les données des entreprises actives dans l'industrie manufacturière française, les résultats montrent un dégrée d'hétérogénéité important par rapport à la technologie des entreprises. De plus, les paramètres technologiques sont identifiés, ce qui permet de mieux reproduire la distribution observée des tailles des entreprises.

1.2.4 Chapitre 5: Sur la régression instrumentale nonparamétrique avec des effets fixes additifs

Le cinquième chapitre est lié au chapitre précédant, puisqu'il consiste en l'estimation économétrique de la fonction de demande inverse - un élément central du modèle de Cournot. En particulier, ce chapitre développe un estimateur instrumental nonparamétrique en prenant en compte des effets fixes non-observés . Dans le cas de la fonction de demande inverse, la vraie relation entre le niveau de prix et le niveau de production est inconnue. Pour cette raison, l'estimation nonparamétrique est une approche prometteuse pour éviter des problématiques liées à la mal-spécification du modèle empirique de la demande inverse. Généralement, l'estimation de la demande inverse représente certains défis économétriques. Premièrement, parce que le niveau de prix ainsi que le niveau de production changent à travers des chocs spécifiques à l'évolution de l'économie (taux de chômage, taux de change) et/ou à travers des chocs spécifiques à l'industrie. Comme ces chocs sont difficiles à modéliser ainsi que probablement corrélés avec la variable dépendante (le niveau de production agrégé) il est naturel de les prendre en compte par des effets fixes non-observés. Deuxièmement, par le mécanisme d'équilibre de l'offre et de la demande, la variable dépendante dans ce modèle, est soupçonnée d'être déterminée en même temps que le niveau de prix, ce qui introduit le biais de simultanéité – s'il n'est pas pris en compte. (Wooldridge, 2016, Chapter 16). La variable dépendante de la fonction de demande inverse est donc l'objet des différentes sources d'endogeneité et dans un tel cas la méthode de régression instrumentale avec des méthodes à effets fixes est requise pour garantir une estimation non-biaisée et convergente. Pour les modèles paramétriques - particulièrement les modèles linéaires - l'application des deux méthodes en même temps est une approche commune (Koebel and Laisney, 2016). En partant d'autres estimateurs nonparamétriques dans la littérature, ce chapitre développe un approche nonparametrique pour différents modèles endogènes en panel, c'est-à-dire avec des effets fixes individuels, temporel et/ou les deux simultanément (Fève and Florens, 2014; Lee et al., 2019; Florens et al., 2018). Les résultats des simulations suggèrent une bonne performance à taille limitée de l'échantillon de l'estimateur nonparametrique proposé. De plus, l'estimateur est appliqué sur des données agrégées des industries manufacturières américaines. Les résultats montrent que la quantité produite n'est pas toujours décroissante dans les prix ce que pointe sur la mal-spécification des modèles paramétriques utilisés dans la littérature et implique également une violation de la loi de demande.

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Chapter 1

General introduction

1.1 Motivation

Industry dynamics can be described as the ongoing process of renewal of an industry. That is, firms enter, grow, shrink, and may finally exit the market, where each individual firm shapes the industry with its activity. There are various measures that can describe the evolution of an industry: the number of active firms, the distribution of firm size, the amount of total production, total employment, and many others. A very suitable way to illustrate industry dynamics might be by considering newly emerging industries, for which some regularities were observed. For instance, emerging industries are characterized by a high rate of firm entry at the beginning, leading to a sharp increase in the number of active firms. As the industry matures, at a certain point, the number of firms decreases what the literature refers to as the shakeout. Less firms prevail in the market by increasing the total level of production of the industry (Smith, 1968; Gort and Klepper, 1982; Klepper and Graddy, 1990; Jovanovic and MacDonald, 1994). Insufficient profitability, i.e. operating costs exceeding revenues, is probably the most important reason why firms cease their operations. A firm's profitability, in turn, is significantly determined by its productivity, which is affected by innovation in the production technology (R&D), quality in production factors, as well as learning by doing (Syverson, 2011). Therefore, unproductive firms are likely to shut down in the long-run, being replaced by more productive incumbent or entering firms. Schumpeter (1942) described this as the process of creative destruction.

For a better understanding of the concept of productivity and why it matters consider the level of production, at the firm or at the industry level. The level of production increases either by using more input factors (capital, labor, and/or materials), or by increasing the efficiency with which these inputs are transformed into output. This latter factor, which grasps changes in output that cannot be explained by changes in inputs, is usually referred to as total factor productivity. Many studies have shown that cross-country differences in output level can in large part be explained by differences in aggregate productivity (Mankiw et al., 1992; Prescott, 1998; Hall and Jones, 1999). Furthermore, increases in productivity have strong effects on the long-term growth and prosperity of an economy (Caselli, 2005). This is because productivity is linked to firms' learning process and innovative activity, which is instrumental, if not indispensable, for sustainable growth both at the micro level (firm) and at the macro level (industry or country). Further, from a welfare perspective, in a competitive environment, a higher level of aggregate productivity decreases costs and, as a result, producers' and consumers' surplus increases.

Productivity is widely regarded as a crucial factor to understand the functioning and the performance of an industry. As such, it will play a key role in this thesis' endeavor to investigate the dynamics of the French manufacturing industry. However, productivity is not a readily observable variable, but typically an unobserved factor in the production process. Catching this unobserved factor is an important research topic in the field of industrial organization (IO) and more specifically in production theory, where a firm's production process is represented by a production function that maps input factors and productivity to output. The firm-level productivity is then derived based on the estimation of the firm's production function. This approach, which today is the established methodology to estimate productivity, will also be followed here. The use of production functions to investigate firms' production behavior has a long tradition in IO and dates back to Cobb and Douglas (1928) who delivered the first formal expression. Other scholars followed as, for instance, Frisch (1935) who studied substitutability of production input factors, Arrow et al. (1961) developed what the literature refers to as the Constant Elasticity of Substitution (CES) production function. Samuelson (1963) and Shephard (1970) presented the concept of duality of production that shows the relation between output maximisation and cost minimization of a firm. For empirical work, both the Cobb-Douglas and the CES production function imply considerable parameter restrictions, seminal works by Diewert (1971) and Christensen et al. (1971) provided more flexible production function specifications. This research is still ongoing, for example, Gandhi et al. (2020) and Demirer (2020) develop fully nonparametric approaches to further relax parameter restrictions.

Once firm-level productivity is consistently estimated, it can be aggregated to investigate the performance of a given economy in terms of its productivity trajectory. In the literature, a widely used measure for aggregate productivity is the weighted average, where firms' productivity is weighted by their output shares (Olley and Pakes, 1996; Van Biesebroeck, 2008). Based on this approach, aggregate productivity can increase for two reasons: (i) if firms increase their individual level of productivity and (ii) if the weights, i.e. the output shares, shift from less to more productive firms. (i) is referred to as within-firm productivity change by learning and (ii) is referred to between-firm change, also known as the process of resource reallocation. Allocative efficiency, in general, has gained a lot of attention in the field of IO, where the fundamental question is by which resource allocation an economy reaches the highest level of aggregate productivity. If, for instance, input factors are allocated to firms with smaller marginal products w.r.t. inputs, resources are less efficiently used and, as a consequence, the aggregate productivity is lower (Restuccia and Rogerson, 2008, 2013; Hsieh and Klenow, 2009). Haltiwanger (2011) describes an economy as "well-working" if the economy features two characteristics: first, static allocative efficiency, i.e. if more productive firms produce more compared to less productive firms and second, dynamic allocative efficiency, if output shares shift from less to more productive firms over time (between-change). In this thesis, the use of an appropriate aggregate productivity decomposition method allows to measure the different effects related to firms' learning, resource reallocation, and firm entry and exit on aggregate productivity growth.

In this context, the thesis also investigates the evolution of firms' market power. Generally, market power describes a firm's ability to set prices above its marginal costs - a gap also known as the markup. Since both output prices and marginal costs are typically unobserved, markups need to be estimated econometrically, thus enabling to conjecture on firms' market power. For that purpose, Hall (1986, 1988) provided an econometric approach to estimating markups at the industry level. This approach relies on the estimation of a production function and highlights its usefulness for empirical work. Building on these works, De Loecker (2011) and De Loecker and Warzynski (2012) provide a methodology to estimate markups at the firm-level. Recently, there has been a vivid discussion on whether there is a systematic increase in market power (Hall, 2018; Traina, 2018; De Loecker et al., 2018; Autor et al., 2020; De Loecker et al., 2020; Demirer, 2020). This is a very important question since changes in market power have implications on secular trends of the economy. For instance, a higher level of markups is associated with lower entry rates, less capital investments and, hence, less innovation, which hampers productivity improvements. It is also shown that the rise in markups explains the decrease in labor share, which is motivated by firms cost minimizing behavior, where higher markups directly reduce firms' demand for labor and capital investment. As a consequence, increasing markups are shown to reduce welfare considerably (Edmond et al., 2018; Berry et al., 2019; Syverson, 2019; De Loecker et al., 2020).

Finally, this thesis explicitly studies firms' cost-efficiency and welfare via a structural competition model. The model incorporates various industry and firm key characteristics such as firms' strategical behavior, heterogeneity in production technology, and market power. As briefly mentioned, in a competitive environment, firms are incentivized to increase their level of efficiency. That is, a lower level of efficiency is related to higher production costs, which, in turn, forces the firm to set higher output prices. As a consequence, compared to more efficient competitors, inefficient firms self-select to exit the market in the long-run. There exist various market equilibrium models in the literature that aim to represent firm competition and the process of market selection (Jovanovic, 1982; Hopenhayn, 1992; Ericson and Pakes, 1995). In this thesis, the well-known Cournot competition model is studied in which firms are assumed to make optimal choices w.r.t. their output quantity, taking into account their technology as well as the production choices of their competitors (Amir, 1996; Amir and Lambson, 2000; Götz, 2005; Ledezma, 2021). Here, firms' technology is represented by their cost function, which maps input prices, the production quantity and unobserved (heterogeneous) cost efficiency to total costs. The analysis of the model yields new microeconomic foundations of firms' strategical behavior in a competitive environment and enables the theoretical and empirical characterization of inefficient and efficient firms. Importantly, the model is also used to investigate welfare effects, where the analysis ultimately boils down to the question at which overall costs (production costs across all firms) an economy produces a given output quantity. And, from the view of a social planer, how individual firms' production needs to be reallocated to minimize overall costs - or, in other words, to maximize overall economic welfare.

1.2 Overview of the thesis

This thesis contributes to the literature by a detailed investigation of the mentioned topics, i.e. the evolution of aggregate productivity and market power, resource allocation, firm entry and exit, and cost-efficiency of firms in a competitive environment. Empirical evidence is derived from the French fiscal firm-level datasets FICUS, from 1994 to 2007, and FARE, from 2008 to 2016. FICUS and FARE refer to "fichier de comptabilité unifié dans SUSE" and "fichier approché des résultats d'Esane", respectively. That is, FICUS was part of the French firm-level database SUSE and was replaced in 2008 by FARE, which, in turn, belongs to the current database Esane. Both are fiscal datasets, i.e. firms are obliged to report information about their balance sheets and income statements.

A short overview of the chapters is stated below. Further down, a more detailed summary for each of the main chapters is provided.

- Chapter 2 investigates aggregate productivity dynamics of the French woodworking industry by taking firm entry and exit into account. Also, aggregate productivity dynamics are related to firms' export behavior.
- Chapter 3 considers the entire French manufacturing industry and studies aggregate productivity and markup dynamics, taking firm entry and exit into account.
- Chapter 4 analyses firm competition à la Cournot and welfare, where firm heterogeneity is introduced via both fixed and variable costs, yielding new theoretical foundations. The model is then econometrically estimated using data from French manufacturing firms.
- Chapter 5 develops an estimator for nonparametric instrumental regression with fixed effects, which is required when estimating, for instance, the inverse demand function

such as presented in Chapter 4. The nonparametric estimator is tested on simulated data as well as on aggregate data of 2-digit U.S. manufacturing industries.

- Chapter 6 concludes and summarizes the thesis.

1.2.1 Chapter 2: Productivity dynamics and exports of the french woodworking industry

The second chapter considers the French woodworking industry as a special case of the French manufacturing industry. More specifically, here aggregate productivity growth is investigated while taking firm entry and exit into account. Firm-level productivity is estimated based on a Cobb-Douglas value added production function, whereupon an appropriate decomposition method is applied to assess the contribution to aggregate productivity growth of those firms that survive, enter, and exit in the woodworking industry. Furthermore, productivity growth is related to firms' export behavior, both in terms of their export status, i.e. either exporter or non-exporter, and in terms of their export and domestic economic activity, i.e. firms' sales volumes in the domestic and in the export market. The motivation to investigate the French woodworking industry, in particular, is that it has become a key industry in coping with current and future challenges linked to climate change and the energy transition, i.e. the reduction of $CO2$ emissions as well as the reinforced demand for renewable resources (Lundmark, 2010). Notably, in 2013 the French government declared the domestic woodworking industry, among others, part of the public action plan *"La Nouvelle France Industrielle"*, aiming to effectively tackle these challenges at a larger scale. As a result, great importance is also assigned to the French woodworking industry, which requires to deepen the understanding of its economic performance and sustainability. Moreover, the analysis of the relation between aggregate productivity and firms' export behavior is motivated by the fact that the trade balance of the French woodworking industry reveals a negative trend over the past decades, accounting for about 10% of France's total trade deficit (Levet et al., 2014). Generally, the degree of forest endowment of a country is an important factor of its comparative advantage in the international trade of wooden products (Lundmark, 2010; Levet et al., 2015). However, even though France is one of the best endowed countries in Europe in terms of forest area, the affiliated industry has not been able to take full advantage of that natural resource endowment.

The results suggest that aggregate productivity of the French woodworking industry grew considerably during the periods 1994-2000 and 2001-2007. However, during the period of economic distress, 2008-2012, the industry's aggregate productivity growth experienced a significant slowdown, which recovered over the period 2012-2016. The most important driver for these dynamics is the contribution of the group of incumbent firms. Further, the separate investigation of aggregate productivity growth w.r.t. firms' export status shows that the aggregate productivity of the group of exporters grows more consistently during different periods compared to non-exporters and that exporting firms and exhibit a 7% to 9% higher median productivity level. When investigating the contribution of firms' domestic and export economic activity to aggregate productivity growth the results show that domestic activity contributes considerably to a decrease in aggregate productivity as the French woodworking industry generates by far the most sales in the domestic market. The results suggest that a more international orientation of the industry, both in terms of the number of exporters and in terms of export intensity, is promising for a higher and more sustainable productivity growth.

1.2.2 Chapter 3: Productivity, markups, entry, and exit: evidence from French manufacturing firms

The third chapter extends the analysis to the entire French manufacturing industry. Besides the evolution of aggregate productivity, this chapter also investigates the evolution of aggregate markups for the period 1994 to 2016 by taking firm entry and exit into account. A further generalization with regard to the first chapter as well as to other approaches in the literature is made by estimating firm-level productivity based on a translog production function, from which markups are derived (De Loecker and Warzynski, 2012; Ackerberg et al., 2015). The investigation of dynamics of both aggregate productivity and markups over such a long period has not yet been performed for the French manufacturing industry and constitutes the main contribution of this chapter. The results show that aggregate productivity in the French manufacturing industry has grown by about 48% from 1994 to 2016. The growth was primarily driven by incumbent firms' productivity improvements rather than by the market entry of high productivity firms or the market exit of low-productivity firms. Confirming other studies for the French economy, the results also reveal a slowdown in aggregate productivity growth, which is mainly induced by a slower reallocation process of output shares among incumbent firms (Cette et al., 2017; Ben Hassine, 2019). Further, while aggregate markups are found to vary over time, the results do not confirm such a systematic increase in markups as recently documented by De Loecker et al. (2020) for the U.S. economy. Here, incumbent (or surviving) firms maintain a considerably higher aggregate level of markups and contribute positively to the aggregate markup. The net entry contribution to overall aggregate evolution of markups reveals a varying sign, where especially entering firms considerably lower the aggregate markup evolution toward the end of the investigated time horizon. Moreover, high markup firms experience a decrease in markups over time, which further contrasts with the findings of De Loecker et al. (2020). Analyzing in a regression framework the relation between markups and various firm characteristics, it is shown that entering firms tend to have lower market power and/or adopt an aggressive price policy to stay in the market.

1.2.3 Chapter 4: Cournot equilibrium and heterogenous firms

The fourth chapter explicitly models competition among firms à la Cournot, where firms optimally chose their output quantity, given their technology and the optimal production choices of their competitors. The model is built on two components: First, the price mechanism described by the inverse demand function, where firms are assumed to be price-takers facing all the same price. Second, firms' technology which is described by their individual cost function, composed of fixed and variable costs. In this chapter both the short and the long-run Cournot equilibrium are characterized, where firms with different technologies, i.e. with heterogeneous fixed and variable costs as well as various degrees of market power in the product market, are considered. Here, the introduction of unobserved heterogeneity in both fixed and variable costs is novel in the literature (Novshek, 1985; Gaudet and Salant, 1991; Okumura, 2015; Götz, 2005; Ledezma, 2021). Furthermore, in a framework with homogeneous firms, Mankiw and Whinston (1986) showed that the long-run Cournot equilibrium may be inefficient due to too many entries. This result is extended to the case of heterogeneous firms, showing that higher industrial concentration of production is welfare improving - provided the regulator is able to control firms' output price. A second part of the chapter seeks to propose an econometric framework to estimate the model, notably the inverse demand and the cost function. Using data of manufacturing firms in France from 1994 to 2016, the empirical results emphasize the importance of both observed and unobserved heterogeneity for explaining firms' cost and marginal revenues. Frequently, fixed costs are found to be very small, but significant for the smallest and largest firm sizes. This may have policy implications, both for increasing the survival probability of small firms and for reducing inefficiencies (or market power) of bigger firms. Unobserved heterogeneity in variable costs translates in a competitive advantage of bigger firms by lowering their variable cost function (ceteris paribus). Here, this type of cost efficiency is shown to be compensated by lack of technological improvement over time for bigger firms.

1.2.4 Chapter 5: Nonparametric instrumental regression with additive fixed effects

The fifth chapter is closely related to the previous chapter by considering the econometric estimation of the inverse demand function, which is an important part of the Cournot competition model. In particular, the chapter develops a nonparametric instrumental estimator by controlling for unobserved fixed effects. The inverse demand function describes the relation between an industry's price and output level. In other words, the inverse demand aims to picture the "law of demand", stating that prices are decreasing in the level of output. Empirically, however, the true functional form of the inverse demand is unknown and, thus, nonparametric estimation is promising in order to avoid misspecification in the used inverse demand model. In doing so, the estimation of the inverse demand function entails various econometric challenges to overcome. First, output prices might be shifted by macroeconomic and industry specific shocks, likely to be correlated with the model's explanatory variable, i.e. the industries' aggregate output level. Since these shocks are difficult to model, it is natural to take them into account by unobserved fixed effects. Second, by the equilibrium mechanism of supply and demand, the explanatory variable is jointly determined with the dependent variable, i.e. the industry's price level is jointly determined with its production level, leading to the simultaneity bias when not taken into account (Wooldridge, 2016, Chapter 16). As a result, in such a case both instrumental variable (IV) and fixed effects (FE) regression techniques are required to cope with the different sources of endogeneity. For parametric models this is a common estimation and identification strategy (Koebel and Laisney, 2016; De Monte and Koebel, 2021). The chapter aims to provide a flexibly applicable nonparametric solution for different kinds of endogenous panel models, that is with individual, time or two ways effects, by combining existing nonparametric kernel regression methods (Fève and Florens, 2014; Florens et al., 2018; Lee et al., 2019). The simulation results suggest good finite sample behavior of the proposed estimator. Further, the estimator is also applied to estimate the inverse demand function, based on price and output data of U.S. manufacturing industries. The estimation results illustrate that prices are not always decreasing in the production level, suggesting a violation of the law of demand and pointing to potential misspecification in static parametric models.

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Chapter 2

Productivity dynamics and exports in the French woodworking industry[1]

2.1 Introduction

Among all manufacturing industries, the woodworking industry is probably the oldest and most traditional one, existing for centuries. At the same time it has become a key industry in coping with current and future challenges linked to climate change and the energy transition, i.e. the reduction of CO2 emissions as well as the reinforced demand for renewable resources (Lundmark, 2010). Notably, in 2013 the French government declared the domestic woodworking industry, among others, part of the public action plan *"La Nouvelle France Industrielle"*, aiming to effectively tackle these challenges on a larger scale.[2] As a result, great importance is also assigned to the French woodworking industry, which requires to deepen the understanding of its economic performance and sustainability.

This chapter seeks to investigate the economic performance and sustainability of the French woodworking industry by analysing aggregate productivity dynamics in the face of firm entry and exit by the application of the Dynamic-Olley Pakes Productivity Decomposition (DOPD, henceforth) (Melitz and Polanec, 2015). In doing so, the effect of reallocation of sales shares among firms on productivity growth is investigated, providing information about the allocative efficiency in the industry. As a second element, the chapter analyses the relationship between aggregate productivity growth and export dynamics. For this purpose, I investigate differences in aggregate productivity growth dynamics w.r.t. firms' export status (i.e. exporting and non-exporting) as well as the volumes of their domestic and export activity. This breakdown is achieved by using appropriate productivity decomposition methods. Aggregate productivity is derived from firm-level total factor productivity

[1]This chapter is based on De Monte, E. (2021), Productivity dynamics and exports in the French woodworking industry, *BETA Working Paper, Université de Strasbourg.* (Submitted)

[2]https://www.gouvernement.fr/action/la-nouvelle-france-industrielle, (April, 2021).

(TFP), which, in turn, is estimated through a Cobb-Douglas value added production function (Ackerberg et al., 2015). To estimate TFP, I use fiscal firm-level data for firms active in the French woodworking industry, over the period 1994-2016. Since it is likely that the structural parameters of the production function change over such a long period, a test for structural stability is applied on the sub-periods 1994-2007 and 2008-2016. My results, point to structural instability between both periods.

Beside the fact that the woodworking industry is an important pillar for coping with environmental challenges, it is also important because of its economic weight within the overall French manufacturing. More precisely, the three big manufacturing sub-sectors of the woodworking industry, the manufacture of wood and wood products, the manufacture of pulp, paper, and paperboard, and the manufacture of furniture, account on average for about 5% of total turnover, 3% of total exports, and 7% of total labour demand of the overall French manufacturing industry. However, during the period from 1994 to 2016, the French woodworking industry has struggled: The shares in turnover and exports relative to the overall French manufacturing industry have decreased over time. Further, compared to 1994, by 2016 the number of active firms and total labour demand has dramatically decreased, by about 30% and 40%, respectively. At the same time, value added production has only slightly increased.[3] These developments raise the serious question of whether the French woodworking industry is sufficiently prepared for and oriented towards future challenges. One important element in answering this question is to shed light on productivity dynamics. To understand why this matters, consider growth in aggregate value added production, which might be induced by either growth in capital (through an aggregate increase in firm investment), labour accumulation, and/or by higher aggregate productivity. The latter component is widely believed to be the most important driver of long-run growth and economic prosperity (Calligaris et al., 2016; Caselli, 2005). For this reason, a detailed investigation of the aggregate productivity trajectory helps to better understand the overall development of an industry.

Generally, for a given industry, aggregate productivity is most frequently measured as a weighted average of all firms' productivity, weighted by their sales shares. Aggregate productivity itself might therefore change for three reasons: (i) firms improve their own productivity, (ii) sales shares shift from less to more productive firms, and (iii) new firms enter the market, crowding out less productive firms. In the literature, (i) is referred to as *within-change* in productivity improvement and/or learning effects, occurring when firms learn to more efficiently transform inputs into output. (ii) is referred to as *between-change*, occurring when sales shares shift between firms through reallocation. From a public welfare point of view, Haltiwanger (2011) describes that an industry is well-working if it shows *allocative efficiency*, distinguishing between static efficiency, i.e. firms with higher productivity

[3] Source: own calculations. See Section 2.5 as well as Appendix 2.10 for further descriptive statistics.

produce more, as well as dynamic allocative efficiency, i.e. over time, sales shift from less to higher productive firms. Economists, therefore, generally consider resource allocation a crucial indicator for the healthiness of an industry.

Beside the analysis of aggregate productivity w.r.t. reallocation effects and entry and exit dynamics, the chapter also aims to investigate the relation between aggregate productivity and international trade. This is motivated by the fact that the trade balance of the French woodworking industry reveals a negative trend over the past decades accounting for about 10% of France's total trade deficit (Levet et al., 2014). The degree of forest endowment of a country is an important factor of its comparative advantage in the international trade of wooden products (Lundmark, 2010; Levet et al., 2015). Even though France is one of the best endowed countries in Europe in terms of forest area, the affiliated industry is not able to take advantage of that property. Instead, comparing the world's most important producer countries of wood products, Koebel et al. (2016) illustrate that the export sales share of the French woodworking industry has decreased between 2000 and 2011. Importantly, in their study they also find a positive relation between an industry's aggregate productivity and its trade balance.

I find that the aggregate productivity of the French woodworking industry grew considerably during the periods 1994-2000 and 2001-2007. Afterwards, during the period of economic distress, 2008-2012, the industry's aggregate productivity growth experienced a significant slowdown, which recovers over the period 2012-2016. The most important driver for these dynamics is the contribution of the group of incumbent firms. Further, the separate investigation of aggregate productivity growth w.r.t. firms' export status shows that the aggregate productivity of the group of exporters grows more consistently during different periods compared to non-exporters and that exporting firms reveal a 7% to 9% higher median productivity level. However, when investigating the contribution of firms' domestic and export economic activity to aggregate productivity growth I find that domestic activity contributes considerably more compared to export activity as the French woodworking industry generates most sales in the domestic market. My results therefore suggest that a more international orientation of the industry, both in terms of the number of exporters and in terms of export intensity, is promising for a higher and more sustainable productivity growth.

The chapter is organized as follows. Section 2.2 reviews the related literature, Section 2.3 presents the empirical framework, Section 2.4 describes the data, Section 2.5 provides descriptive statistics, Section 2.6 presents empirical results of the test for structural stability and the distribution of firm-level productivity, Section 2.7 discusses results of aggregate productivity dynamics, and Section 2.8 concludes.

2.2 Literature review

2.2.1 Productivity and resource allocation

Aggregate productivity increases not only if single firms increase their productivity but also if more productive firms produce more. Moreover, new entering firms replace older and probably unproductive ones, scrapping together with surviving firms the left market shares - also known as the process of creative destruction (Schumpeter, 1942). In the literature effects of firm dynamics, in terms of market entry and exit, on aggregate productivity growth are extensively investigated by the application of various productivity decomposition methods. Baily et al. (1992) develop in their seminal work a productivity growth decomposition that allows to measure the contribution to productivity growth of the group of surviving firms - composed of the contribution through surviving firms' productivity improvement and through reallocation in output shares - as well as the contribution of the group of entering and exiting firms. Investigating the U.S. manufacturing industry for 1972-1982, they find that reallocation of market shares to more productive firms contributes considerably to aggregate productivity growth and that the effect of firm entry and exit is relatively is low. Further, Griliches and Regev (1995) and Foster et al. (2001) develop a very similar decomposition approach in the sense that they trace back firms w.r.t. changes in market shares and productivity. Griliches and Regev (1995) investigate the Israeli manufacturing for 1979-1988 and find that most of the aggregate productivity improvement comes from individual firms' productivity improvements (learning effects), where the net entry contribution to productivity growth is here also measured to be small. Foster et al. (2001) show that the results w.r.t. reallocation and entry/exit effects are sensitive to the methodology in use. Their study shows that reallocation is a very dynamic process varying cyclically with substantial differences across industries, also they show that entering firms have higher productivity compared to exiting firms, sustaining the hypothesis of creative destruction. Foster et al. (2006) analysing the U.S. retail sector in the 90's and show that the largest part of the productivity growth is due to new entering firms, replacing older low productivity firms. Foster et al. (2008) highlight the importance of distinguishing between productivity measured based on physical or revenue output when analysing the effect of entry on aggregate productivity growth. This is because revenue productivity is likely to be positively correlated with firms' prices, i.e. a firm might be considered productive not only because it is cost-efficient but also because of setting high prices. They, therefore, argue that as young entering firms ask lower prices the effect of firm entry to aggregate productivity growth is likely to be underestimated when revenue productivity is used. Baldwin and Gu (2006) apply both the productivity decomposition described by Griliches and Regev (1995) and Foster et al. (2001) on the Canadian manufacturing industry. Both decomposition approaches reveal that most of the aggregate productivity growth is contributed by surviving firms' within productivity improvements. More recently, Melitz and Polanec (2015) present, to my knowledge, the most current productivity growth decomposition incorporating the contribution of surviving firms, reallocation effects, as well as the contribution of firm entry and exits effects. They compare their method with the ones presented by Griliches and Regev (1995) and Foster et al. (2001), and show that their method does more accurately measure the effect of surviving, entering, and exiting firms. Analysing the Slovenian manufacturing from 1995 - 2000, they find that surviving firms contribute considerably more to aggregate productivity growth compared to entrants and exitors. The study also reveals that entrants and exitors contribute negatively and positively, respectively, to aggregate productivity growth. According to their method, this implies that on the aggregate level both the group of entrants and exitors are relatively less productive compared to the group of surviving firms.[4] Note that beside the reallocation of market shares, i.e. the allocation of firms' output within a given industry, productivity is also affected by the allocation of inputs, such as capital and labour. That is, similar to the case of the allocation of output shares, where the highest level of efficiency of a given industry would be attained if the output is produced by the most productive firms, inputs should be allocated to those firms with the highest marginal products w.r.t. to a given input factor. In this sense, Hsieh and Klenow (2009) investigate allocative efficiency of China and India and compare them as a benchmark to the United States. They find if resource allocation in China and India was as efficient as in the United States, both countries would gain in aggregate productivity between 30% - 50%, and 40% - 60%, respectively. Also See Restuccia and Rogerson (2013) reviewing the literature on misallocation and productivity as well as further studies in this stream for Italy (Calligaris et al., 2016) and Latin America (Busso et al., 2013).

2.2.2 Productivity and international trade

Productivity is frequently analysed in the context of international trade in order to investigate the effect of trade policy on the aggregate productivity of a given industry. Generally, there is a consensus in the literature that exporting firms reveal higher productivity compared to firms that are only active on the domestic market. Bernard and Jensen (1999), for instance, find for the U.S. manufacturing a positive correlation between exporting firms and the level of productivity, however, no causal evidence that exporting leads to higher productivity. Bernard and Jensen (2004) show that firms' past business success plays an important role for firms' decision to start export activity, indicating that exporting firms are already more productive, prior to engage in exporting.[5] Melitz (2003) presents a dynamic industry

[4] This issue is discussed more in detail in Section 2.3.2.

[5] See Bernard et al. (2003) embedding firm characteristics w.r.t. productivity and export status in a macro model to investigate the effect of globalization and other factors on productivity, firm entry and exit. Bernard et al. (2007) discuss further theoretical and empirical aspects w.r.t. firms and international trade.

model with heterogeneous firms and draws the theoretic link between aggregate productivity improvements and international trade. In this model, firms that are more efficient compared to their competitors self-select to export, whereas less efficient firms remain in the domestic market, shrink, and finally exit. Hansson and Lundin (2004) studying Swedish manufacturing firms in the 1990s confirm both a considerable advantage in productivity for exporting firms and a higher productivity level prior to start export activity. Pavcnik (2002) shows for the Chilean manufacturing industry that firms active in industries where goods are internationally traded improve more in terms of productivity compared to firms active in industries with no international trade. Melitz and Ottaviano (2008) develop a monopolistic model of trade with heterogeneous firms and find that aggregate productivity (average markups) are positively (negatively) related to the size of the market and to the extend the market is integrated to international trade.[6] Harris and Li (2008) investigate firms in the UK active both in the manufacturing and service sector. They apply the aggregate productivity decomposition proposed by Foster et al. (2001) and show that exporting firms contribute more to overall UK productivity growth compared to non-exporting firms. De Loecker (2013) provides further empirical evidence using Slovenian micro data and shows that firms take a substantial advantage in terms of productivity improvement when entering to export.

2.2.3 Studies with focus on France and/or the woodworking industry

There are several studies particularly related to France in terms of productivity as well as to the woodworking industry. Bellone et al. (2008) investigates productivity patterns of firms active in the French manufacturing after entry to export. Using firm-level data covering the period 1990-2002, they find that firms first tend to suffer from a decrease in productivity whereupon productivity increases, arguing that the positive effects from the entry to foreign market is not immediate but lags back. Bellone et al. (2014) investigate productivity differences w.r.t. firms' export status, both for the French and Japanese manufacturing. They show, among other results, that firms' export status matters when it comes to differences to differences in productivity between both countries. Cette et al. (2017) report a detailed analysis of the evolution of the productivity of firms active in the French economy. They find an ongoing productivity slowdown from 2000 on and point to inefficient reallocation mechanisms in the economy.[7] Ben Hassine (2019) investigates the French manufacturing and service industry in terms of aggregate productivity growth before and after the economic and financial crisis in 2007. Applying various decomposition methods he shows that there was only low aggregate productivity growth before the crisis and a decline after. Using different productivity decomposition methods he finds that aggregate productivity growth is mainly driven by individual firms' productivity improvement (learning effect or within

[6] A firm's markup is defined as the gap between its output price and its marginal costs.
[7] Also see Bellone (2017) for a detailed discussion on the findings presented in Cette et al. (2017).

contribution). After the crisis the within contribution is even negative, which is interpreted by the author as firms' difficulties to adapt to the changing economic environment.[8] Similarly, De Monte (2021) estimates aggregate productivity growth for French manufacturing firms over the period 1994-2016. He also finds a slowed aggregate productivity growth from 2000 on, which is mainly induced by incumbent firms' slowed reallocation process of output shares, and that net entry contributes considerably less to aggregate productivity growth compared to the contribution of incumbent firms.

Turning to more specific studies on the woodworking industry, Lundmark (2010) illustrates the fast growth of international trade for forest products in Europe, where he highlights that the growth is not only due to economic growth in general but is also induced by the ongoing process of European integration, an improved transport infrastructure as well as the new demand for biofuel with regard to the energy transition. Lundmark (2010) also investigates the effect of forest endowment on the trade balance of a country, suggesting that forest endowment is a crucial factor for explaining differences in net trade between countries. That is, for a given country, a higher level of forest endowment should lead to an increase the trade balance (export - imports). Levet et al. (2014) show that the trade balance of the French woodworking industry is negative, accounting for about 10% of France's total deficit. Since France is one of the best endowed countries in Europe in terms of forest surface, they speak about the French paradox: a highly negative trade balance in spite of a high degree of forest endowment. Obviously, the competitiveness of an industry is also an important determinant for success in the international market. Levet et al. (2015) present a first study on this issue, specific to the French woodworking industry. They identify various aspects impacting the industry's competitiveness: (i) *resource endowment*, i.e. a higher level of resource endowment for a given country should translate into more exports, (ii) *domestic demand*, i.e. a higher domestic demand is expected to be negatively related with the industry's export intensity, and (iii) *aggregate productivity*, i.e. the higher an industry's total factor productivity, the higher its exports. Koebel et al. (2016) compare the most important European countries for trading wood products, covering the period 1995 to 2007, and also find that resource endowment as well as aggregate productivity plays a significant role in explaining the differences in net trade between countries.

2.3 Empirical framework

In this section I present the analytical framework of the chapter. More precisely, I first present the specification and estimation procedure of the Cobb-Douglas value added production function, to finally obtain firm-level productivity estimates. Second, I illustrate the methodology to measure aggregate productivity growth linked to firm entry and exit, i.e.,

[8] Note that the French woodworking industry is not included in that study.

presenting the Dynamic Olley-Pakes Productivity Decomposition. In this section I also introduce how the relation between aggregate productivity growth and firms' exporting behavior is investigated.

2.3.1 Production function estimation

Consider a given manufacturing sector with N firms, indexed by n at time t. I suppose that firms transform inputs into value added output according to a Cobb-Douglas value added production function, given by

$$q_{nt} = \beta_L l_{nt} + \beta_K k_{nt} + \omega_{nt} + \epsilon_{nt}, \tag{2.1}$$

where q_{nt}, l_{nt}, and k_{nt} denote the log of value added production, labor, and capital input, respectively. Further, ω_{nt} denotes (unobserved) total factor productivity (TFP) and ϵ_{nt} is an error term. To consistently estimate the technology parameters, β_L and β_K, one needs to deal with the well-known endogeneity issues linked to the estimation of firm-level production functions. That is, since firms' productivity ω_{nt} is supposed to be known by firms (but unknown to the econometrician), firms' input choices are potentially correlated with ω_{nt}.[9] To overcome this problem I follow Ackerberg et al. (2015) (ACF, henceforth), using a proxy variable approach which consists in modeling material input as a function of a firm's capital input and productivity, i.e. $m_{nt} = h(k_{nt}, \omega_{nt}, \mathbf{c}_{nt})$. Thus, material input is called a proxy variable for unobserved productivity.[10] Note that $\mathbf{c}_{nt}$ is a vector of control variables affecting the optimal choice of material input. As I aim to capture differences in productivity related to market entry and exit and firms' export status, the according dummy variables as well as time dummy variables are used as controls.[11] By supposing that m_{nt} is strictly monotonic in ω_{nt}, we can take the inverse and write $\omega_{nt} = h^{-1}(k_{nt}, m_{nt}, \mathbf{c}_{nt})$. A further key assumption is that productivity follows a first-order Markov process, i.e.

$$\omega_{nt} = g(\omega_{n,t-1}, x_{nt}, exp_{nt}) + \xi_{nt}, \tag{2.2}$$

[9] Correlation between ω_{nt} and, for instance, labour demand l_{nt} might come through firms' anticipation of the realized productivity and the accordingly adjusted (flexible) labor demand. That is, firms' take their productivity, ω_{nt}, into account when optimally choosing their input quantities. Therefore, if we aggregated the two error components into a single, i.e. $u_{nt} = \omega_{nt} + \epsilon_{nt}$, u_{nt}, would likely be correlated with the input factors through ω_{nt}, leading to biased estimates when OLS is used.

[10] Also see Olley and Pakes (1996) (OP) who propose to use firms' investment as proxy variable for unobserved firm productivity. Instead Levinsohn and Petrin (2003) (LP) propose to rather use material inputs arguing that firms' investment might often be zero in the data, especially for small firms. While both OP and LP propose a semiparametric two step estimation approach (which is also the case for the ACF method, used in this chapter) Wooldridge (2009) develops a one-step parametric estimation approach. Blanchard and Mathieu (2016) compare the methods OP, LP, and ACF, using a Cobb-Douglas production function, and find that the estimated coefficients are robust w.r.t. the method in use.

[11] See De Loecker and Warzynski (2012) for a detailed discussion on the use of control variables in the context of production function estimation.

where $g(\cdot)$ denotes the productivity process that depends on a firm's lagged productivity, its exit decision as well as its export status. In particular, $x_{nt} = 1$ if the firms exits in the subsequent period and zero else, $exp_{nt} = 1$ if a firm exports and zero else. The exit dummy is included to control for self-selected exit (Olley and Pakes, 1996). The inclusion of the export dummy allows that exporting might impact firms' productivity and thus also controls for potential self-selection biases w.r.t. firms' export decision (De Loecker, 2013). Further, ξ_{nt} is called the innovation to productivity. By this setting, the estimation of the parameters of interest, β_L and β_K, is done in a two-step semiparametric procedure: First, replacing the productivity term in equation (2.1) by its proxy variable yields

$$\begin{aligned} q_{nt} &= \beta^L l_{nt} + \beta_K k_{nt} + h^{-1}(k_{nt}, m_{nt}, \mathbf{c}_{nt}) + \epsilon_{nt}, \\ &= \Phi(l_{nt}, k_{nt}, m_{nt}, \mathbf{c}_{nt}) + \epsilon_{nt}. \end{aligned} \tag{2.3}$$

where $\Phi(l_{nt}, k_{nt}, m_{nt}, \mathbf{c}_{nt}) \equiv \beta^L l_{nt} + \beta_K k_{nt} + h^{-1}(k_{nt}, m_{nt}, \mathbf{c}_{nt})$. Estimating in this first step $\Phi(\cdot)$ by means of nonparametric kernel regression allows to define unobserved productivity as a function of the parameters of interest as

$$\omega_{nt}(\beta_L, \beta_K) = \widehat{\Phi}(l_{nt}, k_{nt}, m_{nt}, \mathbf{c}_{nt}) - \beta_L l_{nt} - \beta_K k_{nt}. \tag{2.4}$$

Obtaining the innovations in productivity, ξ_{nt} by regressing $\omega_{nt}(\beta_L, \beta_K)$ on $(\omega_{n,t-1}(\beta_L, \beta_K), x_{nt}, exp_{nt})$, the parameters can be estimated in a second step using GMM, imposing the following moment conditions

$$E\left(\xi_{nt}(\beta_L, \beta_k)\begin{pmatrix} l_{n,t-1} \\ (l_{n,t-1})^2 \\ k_{it} \end{pmatrix}\right). \tag{2.5}$$

Note that the instruments, $l_{n,t-1}$, $(l_{n,t-1})^2$ and k_{it}, are chosen by the so called timing assumptions: Capital and labor input are assumed to be fixed and flexible, respectively, where the latter is potentially correlated with the innovation. For this reason, lagged values are used as instruments. I use these three instruments to test for over-identification restriction, however, there are many other candidate instruments, such as material inputs, interacted variables and higher polynomials (Hansen, 1982; Donald et al., 2009).[12]

Firm-level productivity can then be recovered from the parameter estimates, given by

$$\widehat{\omega}_{nt} = q_{nt} - \widehat{\beta}_L l_{nt} - \widehat{\beta}_K k_{nt} - \widehat{\epsilon}_{nt}, \tag{2.6}$$

where $\widehat{\epsilon}_{nt}$ is obtained from the first step estimation, shown in equation (2.3).[13]

[12] See Appendix 2.11.2, Table 2.16, presenting the results of the production function estimation. The table also contains information of the J-Test/Hansen test for overidentification restrictions/validity of the instruments.

[13] That is, $\widehat{\epsilon}_{nt} = q_{nt} - \widehat{\Phi}(l_{nt}, k_{nt}, m_{nt}, \mathbf{c}_{nt})$. See Appendix 2.11.3 for information on the distribution of $\widehat{\epsilon}_{nt}$.

Testing for structural stability

The production function specified in (2.1) is estimated for each 4-digit sector separately. Furthermore, since it is likely that the technological parameters change over time I estimate the production function parameters for two periods, 1994-2007 and 2008-2016, and test for differences in the parameters, which is also referred as testing for structural stability. For a given 4-digit sector, let $\widehat{\beta}_j = (\widehat{\beta}_{L,j}, \widehat{\beta}_{K,j})'$ with $j = \{1, 2\}$ be the estimated production function parameters associated with the two sub-periods. To test for structural stability I apply a Wald-type test with the test statistic given by

$$W_T = \left(\widehat{\beta}_1 - \widehat{\beta}_2\right)' (\widehat{V}_1 + \widehat{V}_2)^{-1} \left(\widehat{\beta}_1 - \widehat{\beta}_2\right), \tag{2.7}$$

where $\widehat{V}_1$ and $\widehat{V}_2$ are the bootstrapped (2×2) variance-covariance matrices belonging to $\widehat{\beta}_1$ and $\widehat{\beta}_2$, respectively. The test statistic W_T follows a $\chi^2(r)$ distribution, with $r = 2$ a degree of freedom equal to the number of parameter restrictions (Andrews and Fair, 1988).

2.3.2 Aggregate productivity growth, firm entry and exit, and export status

The chapter's motivation and contribution is its detailed analysis of aggregate productivity dynamics and its decomposition w.r.t. different groups of firms. In particular, I aim to show to which extend the groups of survivors, entrants, and exitors, contribute to aggregate productivity growth. Moreover, I aim to relate aggregate productivity growth to firms' export behavior. In the following I present the decomposition methods to achieve these objectives. Note that for notational convenience, I drop the hat over $\widehat{\omega}_{nt}$, denoting the estimate of firms' productivity level, described in (2.6).

Aggregate productivity decomposition w.r.t. market entry and exit

Olley and Pakes (1996) present a static approach to measure aggregate productivity for a given industry and year, by

$$\begin{aligned}\Omega_t &= \sum_n^{N_t} s_{nt}\omega_{nt} = \overline{\omega}_t + \sum_n^{N_t} (s_{nt} - \overline{s}_t)(\omega_{nt} - \overline{\omega}_t) \\ &= \overline{\omega}_t + N_t cov(s_{nt}, \omega_{nt}),\end{aligned} \tag{2.8}$$

where the first equality is the weighted average productivity, weighted by firms' sales shares, s_{nt}. The second and third equality separates the weighted average into and unweighted productivity average, $\overline{\omega}_t = N_t^{-1} \sum_{n=1}^{N_t} \omega_{nt}$, and the covariance between firms' productivity and their sales share. Note that N_t denotes the number of active firms for a given industry at t and $\overline{s}_t = 1/N_t$ the average sales share. Considering the aggregate productivity growth between two periods, i.e. $\Delta\Omega = \Omega_t - \Omega_{t-1}$, it can be shown that the growth is transmitted by individual firms' productivity improvement, i.e. by a change in the unweighted average productivity $\Delta\overline{\omega}$, and by sales share reallocation among firms, i.e by a change in the covariance of sales shares and firm level productivity $\Delta cov(s_{nt}, \omega_{nt})$. Aggregate productivity growth induced by individual firms' productivity improvements and sales share reallocation is referred to "within-change" and "between-change", respectively. In a dynamic setting, where firm entry and exit is taken into account, $\Delta\Omega$ can be expressed by the sum of changes in aggregate productivity w.r.t. the groups of surviving, entering and exiting firms. To measure the contribution of each group I adopt the Dynamic Olley-Pakes Decomposition (DOPD, henceforth) (Melitz and Polanec, 2015).[14] As already pointed out by Griliches and Regev (1995), entering and exiting firms can have a positive or negative contribution to aggregate productivity depending on the considered reference level of productivity. For instance, if the reference level is given by the aggregate productivity of surviving firms, entering firms reduce the overall aggregate productivity if that group's aggregate productivity is lower than the aggregate productivity of the group of surviving firms. Similarly, the disappearance of a group of exiting firms will reduce the overall aggregate productivity if that group's aggregate productivity is higher compared to the aggregate productivity of the reference group of surviving firms. In that spirit, the DOPD approach models aggregate productivity with entry and exit in the following way: Let $S_{Gt} = \sum_{n\in G} s_{nt}$ denote the aggregate sales share of a group G, where $G = (E, S, X)$ indexes the group of entrants, survivors, and exitors. A group's aggregate productivity is then defined by $\Omega_{Gt} = \sum_{n\in G} (s_{nt}/S_{Gt})\, \omega_{nt}$. Considering the aggregate productivity of two periods, where the aggregate productivity at $t = 1$ and at $t = 2$, Ω_1 and Ω_2, is given by

$$\Omega_1 = S_{S1}\Omega_{S1} + S_{X1}\Omega_{X1} = \Omega_{S1} + S_{X1}(\Omega_{X1} - \Omega_{S1}) \tag{2.9}$$

$$\Omega_2 = S_{S2}\Omega_{S2} + S_{E2}\Omega_{E2} = \Omega_{S2} + S_{E2}(\Omega_{E2} - \Omega_{S2}). \tag{2.10}$$

That is, Ω_1 is composed of the weighted sum of aggregate productivity of the groups of firms surviving and exiting until $t = 2$. Instead, Ω_2 is composed of the weighted aggregate productivity of the firms having survived and the new firms that have entered the market at $t = 2$. Taking the difference between (2.9) and (2.10) we obtain the growth in aggregate productivity between two arbitrary time points, given by

$$\begin{aligned}\Delta\Omega &= \underbrace{(\Omega_{S2} - \Omega_{S1})}_{\text{Survivors}} + \underbrace{S_{E2}(\Omega_{E2} - \Omega_{S2})}_{\text{Entrants}} + \underbrace{S_{X1}(\Omega_{S1} - \Omega_{X1})}_{\text{Exitors}} \\ &= \Delta\overline{\omega}_S + \Delta N_S cov_S + S_{E2}(\Omega_{E2} - \Omega_{S2}) + S_{X1}(\Omega_{S1} - \Omega_{X1}).\end{aligned} \tag{2.11}$$

[14] See De Monte (2021) for an application of the DOPD approach on various French 2-digit manufacturing industries.

Here, the contribution of surviving firms is further decomposed into the within- and between-change, derived by Olley and Pakes (1996). As can be seen, entrants only contribute positively to aggregate productivity change if their aggregate productivity at $t = 2$ is higher compared to the aggregate productivity of survivors at $t = 2$ $(\Omega_{E2} - \Omega_{S2})$. The group of exitors only contribute positively to aggregate productivity change if their aggregate productivity at $t = 1$ is lower compared to the aggregate productivity of surviving firms at $t = 1$ $(\Omega_{S1} - \Omega_{X1})$.

Aggregate productivity decomposition w.r.t. firms' export status and firms' export activity

As a first step, to relate aggregate productivity growth to firms' export status, I apply equation (2.11) separately to the group of non-exporters and exporters. In this way it can be investigated how aggregate productivity grows within each of the two firm types, and to which extend firm survival, entry, and exit affects or contributes to the aggregate growth. This approach is very much in line with Harris and Li (2008), who only use a slightly different productivity decomposition. However, most exporting firms realize the highest share output sales in the domestic market. To disentangle the contribution of domestic and export activity to aggregate productivity growth I adapt the Olley-Pakes productivity decomposition. As presented in equation (2.8), aggregate productivity of a given industry is measured by a weighted average, where firms' sales shares, s_{nt}, serve as weights. Here, a firm's sales share is measured by its gross output over the industry's total output - where deflated sales are used as proxy for gross output. Generally, a firm's total amount of output is distributed through domestic and export activity, say Y^d_{nt} and Y^{exp}_{nt}, respectively. Therefore, a firm's sales share is composed of the share related to domestic and export activity, too. Formally,

$$s_{nt} = \frac{Y^d_{nt}}{Y_t} + \frac{Y^{exp}_{nt}}{Y_t} = s^d_{nt} + s^{exp}_{nt}, \tag{2.12}$$

where $Y_t = \sum_n^{N_t}(Y^d_{nt} + Y^{exp}_{nt})$ denotes total sales of a given industry at t. Firms that are only active in the domestic market are characterized by $s^d_{nt} > 0$ and $s^{exp}_{nt} = 0$. Plugging (2.12) into (2.8), we obtain

$$\begin{aligned}
\Omega_t &= \sum_n^{N_t}(s^d_{nt} + s^{exp}_{nt})\omega_{nt} \qquad\qquad (2.13)\\
&= \sum_n^{N_t} s^d_{nt}\omega_{nt} + \sum_n^{N_t} s^{exp}_{nt}\omega_{nt}\\
&= \underbrace{N_t\bar{s}^d_t\bar{\omega}_t + \sum_n^{N_t}\left(s^d_{nt} - \bar{s}^d_t\right)(\omega_{nt} - \bar{\omega}_t)}_{\Omega^d_t} + \underbrace{N_t\bar{s}^{exp}_t\bar{\omega}_t + \sum_n^{N_t}\left(s^{exp}_{nt} - \bar{s}^{exp}_t\right)(\omega_{nt} - \bar{\omega}_t)}_{\Omega^{exp}_t}
\end{aligned}$$

where Ω_t^d and Ω_t^{exp} denote the parts of an industry's aggregate productivity generated from firm's domestic and export activity. Each of these two components is further decomposed into a simple average productivity term, weighted by the respective groups sales share, given by ($N_t\bar{s}_t^i$ with $i = \{d, exp\}$), and the covariance term. Note that while it is possible to disentangle a firm's sales share into the part related to domestic and export activity, its productivity cannot be separated into these two components since it is measured based on its overall output (value-added).

Aggregate productivity growth based on the decomposition shown in the third equality of equation (2.13) is determined by taking the difference between two arbitrary points in time, $t = 2$ and $t = 1$, which yields

$$\begin{aligned}\Delta\Omega &= \Omega_2 - \Omega_1 \qquad (2.14)\\ &= \underbrace{\Delta N\bar{s}^d\overline{\omega}}_{W^d} + \underbrace{\Delta\sum_{n=1}^{N}\left(s_n^d - \bar{s}^d\right)(\omega_n - \overline{\omega})}_{B^d} + \underbrace{\Delta N\bar{s}^{exp}\overline{\omega}}_{W^{exp}} + \underbrace{\Delta\sum_{n=1}^{N}\left(s_n^{exp} - \bar{s}^{exp}\right)(\omega_n - \overline{\omega})}_{B^{exp}},\end{aligned}$$

where W^i and B^i with $i = \{d, exp\}$ denote the within and between contribution to aggregate productivity, related to firms' domestic and export activity. If between two periods, the aggregate sales shares of domestic and export activity remains constant, an increase in the unweighted average productivity, i.e. $\Delta\overline{\omega} > 0$, yields positive within contribution of both domestic and export activity. However, if, for instance, the aggregate sales shares sufficiently decreases, an increase in the average productivity might be absorbed by that change in aggregate sales share.[15] An important remark is that when applying this decomposition, I only consider firms that have survived in the market between $t = 1$ and $t = 2$. In this way, growth contribution and reallocation effects among firms active in the domestic and export market are not affected by the appearance of new entering firms.

2.4 Data and variables

I use French fiscal firm-level data of firms active in the woodworking industry, covering the period 1994 - 2016. Table 2.1 below lists the considered 4-digit sectors. The choice of the 4-digit sectors is made in order to cover a representative part of both the first level of wood

[15] Consider the following simple example. The log average productivity, common for both domestic and export activity, is given by $\overline{\omega}_{t-1} = 1$ and $\overline{\omega}_t = 1.1$, representing a 10% increase. The constant aggregate sales share for domestic and export activity are given by $N_t\bar{s}_{t-1}^d = N_t\bar{s}_t^d = 0.7$ and $N_t\bar{s}_{t-1}^{exp} = N_t\bar{s}_t^{exp} = 0.3$, respectively. Hence, $W^d = 0.7 \cdot 1.1 - 0.7 \cdot 1.0 = 0.07$ and $W^{exp} = 0.3 \cdot 1.1 - 0.3 \cdot 1.0 = 0.03$, where $W^d + W^{exp} = 0.1$. If, however, aggregate sales shares also change, for example, the aggregate export share drops from 0.3 at $t-1$ to 0.2 at t, then we obtain $W^d = 0.8 \cdot 1.1 - 0.7 \cdot 1.0 = 0.18$ and $W^{exp} = 0.2 \cdot 1.1 - 0.3 \cdot 1.0 = -0.08$. That is, the drop in export activity absorbs the productivity improvement, leading to a negative within contribution related to export activity.

transformation - given by the manufacture of wood, and products of wood and cork - and the second level of wood transformation - i.e. the manufacture of pulp, paper, and paperboard as well as the manufacture of furniture. The data contains information based on firms' balance sheet and income statement, where each firm is identified by a specific identification number (code siren). Moreover, the data is composed of the two fiscal datasets FICUS (1994 - 2007) and FARE (2008 - 2016). It is important to mention that in 2008 the French Institute of Statistics (INSEE) made significant modifications w.r.t. the 4-digit sector nomenclature firms belong to. That is, the sector a firm belongs to is differently classified in FICUS (according to NAF, révision 1) and FARE (according to NAF, révision 2, 2008).[16] To maintain the current nomenclature used in FARE throughout the whole period, i.e. from 1994 to 2016, I adopt the following method: I first calculate transition probabilities of those firms observed both in FICUS and FARE. That is, I calculate the probability of firms transiting from a specific sector of the former nomenclature (until 2007) to the current nomenclature (from 2008 on). The obtained transition probabilities are then used to assign to those firms that are only observed in FICUS (in case of firm exit before 2008) by probability the current sector classification. In this manner I obtain a sample consistent in the current 4-digit sector classification throughout the whole sample period, allowing to trace back a sector's evolution until 1994.[17] Note that I only consider firms that report at least 5 employees in order to prevent estimates to be distorted by the very large number of small firms, likely to contain measurement errors. In addition, I only keep firms reporting positive values in value added, capital, and materials, which is motivated by the fact that these variables are required to be positive to estimate the logarithmized Cobb-Douglas value added production function. In doing so, for the period 1994-2016, the treated sample contains 13,509 firms summing up to 112,159 observations (see Table 2.1). This represents about 85% of total value added production and about 95% of total turnover w.r.t. the total woodworking industry.[18]

[16] Note that FICUS and FARE refer to "fichier de comptabilité unifié dans SUSE" and "fichier approché des résultats d'Esane", respectively. That is, FICUS was part of the French firm-level database SUSE. In 2008, FICUS was replaced by FARE, which, in turn, belongs to the database Esane. The French industry classification NAF refers to "nomenclature d'activités françaises".

[17] See Appendix 2.9.1 for a more detailed description of the combination of the data sets FICUS and FARE, where also an exemplary transition matrix is presented.

[18] See Appendix 2.9.2 for details on the raw data, illustrating the loss of observations when only keeping firms reporting at least 5 employees.

Table 2.1: Description of 4-digit woodworking sectors

Sector^{a,b}	Description	# Firms	# Obs.
16	**Manufacture of wood and products of wood and cork**		
1610	Sawmilling and planning of wood	2,463	21,778
1621	Manufacture of veneer sheets and wood-based panels	197	1,923
1622	Manufacture of assembled parquet floors	48	360
1623	Manufacture of other builders' carpentry and joinery	1,825	14,396
1624	Manufacture of wooden containers	1,276	11,846
1629	Manufacture of other products of wood	722	5,670
17	**Manufacture of pulp, paper, and other products of paper**		
1711	Manufacture of pulp	14	128
1712	Manufacture of paper and paperboard	270	2,532
1721	Manufacture of corrugated cardboard/cardboard/paper packaging	1,021	10,549
1722	Manufacture of paper products of domestic/health usage	90	718
1723	Manufacture of paper stationery	216	1,993
1724	Manufacture of wallpaper	16	132
1729	Manufacture of other products paper/cardboard	511	5,146
31	**Manufacture of furniture**		
3101	Manufacture of office and shop furniture	1,186	10,044
3102	Manufacture of kitchen furniture	625	5,004
3109	Manufacture of other furniture	3,029	19,940
Total		13,509	112,159

a) Statistical classification of economic activities in the European Community, Rev. 2 (2008)

b) Because of a low number of observations the following sectors are aggregated: 1621 and 1622 (1621/22), 1711 and 1712 (1711/12), 1721 and 1722 (1721/22), as well as 1723, 1724, and 1729 (1723/24/29).

2.4.1 Production function and export variables

Since I am mainly interested in the estimation of a value added Cobb-Douglas production function to recover firm-level productivity estimates, I describe in the following the variables necessary for this purpose. Beginning with the production input factors. Firms' log capital stock, labor, and intermediary products (materials), denoted by k_{nt}, l_{nt}, and m_{nt}, consists in firms' log amount of tangible assets, number of workers, and intermediary products consumption. The latter is given by the sum of firms' expenditures for both raw materials and intermediary products. Firms' (deflated) value added production is denoted by $Q_{nt} = Y_{nt} - M_{nt}$, where Y_{nt} and M_{nt} represent firms' (deflated) gross output (firms' reports on annual sales) and materials. Note that q_{nt} denotes the log value of firms' value added output. Y^d_{nt} and Y^{exp}_{nt} denote a firm's sales on the domestic and export market. A firm is called and exporter only if $Y^{exp}_{nt} > 0$.[19] For the year 2008 firms' export values are not available from the data. This year will therefore be excluded for the analysis related to aggregate

[19] Note that to obtain real values I deflate all monetary variables by a corresponding 2-digit industry price index. For each firm and industry, I know the imbrication $n \in \mathcal{N}_4 \subseteq \mathcal{N}_2$, where $\mathcal{N}_2$ and $\mathcal{N}_4$ denote the set of firms within the 2- and 4-digit sectors respectively. The sectoral price data are available at https://www.insee.fr/fr/statistiques/2832666?sommaire=2832834, (April, 2021).

productivity growth and firms' export behavior.

2.4.2 Definition of firm entry and exit

Definition of entry and exit year by year

The number of firms in the data varies for three reasons: first, firm entry and exit, second temporal inactivity and third, nonresponse. The latter reason is not frequently observed since firms' participation in the survey is mandatory. Instead, temporal inactivity, i.e. cases in which firms are not observed for given interval, whereupon they reactivate their activity, is more frequently observed. However, the data also shows that this is more often the case for shorter intervals. In order to allow consistent analysis on firm entry and exit I adopt the following approach:[20] Let $a_{nt} \in \{0,1\}$ be a binary variable, taking the value 0 in case of inactivity, and 1, if the firm is active. A firm is said to be active at t, if it reports nonmissing or nonzero data for one of the following variables: total production, sold production, turnover, and net profit. In all other cases the firm is supposed to be inactive. Further, survival is denotes by $s_{nt} \in \{0,1\}$ with $s_{nt} = 1$ if $a_{n,t-1} = a_{nt} = a_{n,t+1} = 1$. Entry is denoted by $e_{nt} \in \{0,1\}$ with $e_{nt} = 1$ if $a_{n,t-1} = 0$ and $a_{nt} = a_{n,t+1} = 1$. Exit is denoted by $x_{nt} \in \{0,1\}$ with $x_{nt} = 1$ if $a_{n,t-1} = a_{nt} = 1$ and $a_{n,t+1} = 0$. The status of firms that are active between two periods of inactivity is not identified since the firm could both entrant and exitor. For this case I define $u_{nt} \in \{0,1\}$ and takes the value 1 if $a_{n,t-1} = 0$, $a_{nt} = 1$ and $a_{n,t+1} = 0$.[21]

Definition of entry and exit between time-spans longer than one year

The above method to define entry and exit is based on a yearly basis, which is a very useful measure for presenting entry and exit patterns from year to year, as we will see in the following section. However, since it would take two much space to present all results as, for instance, aggregate productivity growths rates on a yearly basis over the whole sample period, I will provide results spanning over periods longer than one year. For this purpose I need to slightly extend the above definition of entry and exit to the case of entry and exit over time spans longer than one year: Let t_1 and t_2 be two periods in time with $t_1 < t_2$. A firm is defined as a survivor from t_1 to t_2 if the firm is active both at t_1 and at t_2. Furthermore, a firm is defined as an exitor if the firm has exited the market, i.e. $x_{nt} = 1$, for some t with $t_1 \leq t < t_2$ and if the firm was active at t_1 but inactive at t_2. Moreover, a firm is defined as an entrant if the firm has entered the market, i.e. $e_{nt} = 1$, for some t with $t_1 < t \leq t_2$ and if the firm was inactive at t_1 but active at t_2.

[20] See Blanchard et al. (2014) for a similar approach.

[21] Note that $u_{nt} = 1$ if and only if $s_{nt} = e_{nt} = x_{nt} = 0$, that is, the firm is not identified as survivor, entrant or exitor.

Remark 1. It is important to notice that the year by year definition for firm entry and exit, presented in Section 2.4.2, does not identify any surviving, entering or exiting firm for the very first and last year of the sample period, i.e. 1994 and 2016. Instead, the definition for firm entry and exit between longer time periods, presented in Section 2.4.2, allows to identify those firms that survive and exit from the initial year until the last year of a given period as well as to identify those firm that enter between the initial and the last year. This is important in particular for the analysis of the DOPD described in Section 2.3.2.

Remark 2. Firms that fall below or pass over the threshold of five employees are not counted as entrants or exitors. That is, firms' activity status of survivor, entrant, or exitor is determined before dropping any observation, guaranteeing not to count abundant firm entry and exit.

2.5 Descriptive statistics

This section provides some descriptive statistics to present the treated data, highlighting the most important variables for the purposes of the study. Table 2.2 presents averages over all years (1994-2016) w.r.t. firm size groups. The table shows that the share of firms in the sample is decreasing in firm size. The largest share of firms is represented by the group reporting between 5 and 9 employees, given by about 37%. Instead, the group of large firms, reporting 500 employees and more, represents less than 1% of all firms in the sample. The firm size group between 20 and 49 employees detain the largest share of workers in the sample, given by about 19%, followed by the group with 500 and more employees, representing about 18%. Also, it can be seen that this latter group detains the largest share of turnover, given by about 24%. The table also shows that average entry and exit rates are decreasing in firm size. Instead, the rate of exporters, i.e. the percentage of exporting firms, increases in firm size.

Table 2.2: Summary statistics w.r.t. firm size: averages from 1994-2016[a,b]

Size group[c]	# of firms	Share of firms	Share of empl.	Share of turnover	Entry rate	Exit rate	Share of exporters	Age
5-9	1746	37.40	6.77	4.14	5.11	5.02	27.40	16.02
10-19	1201	25.73	9.46	6.66	4.04	4.54	45.20	19.26
20-49	1081	23.16	19.43	15.47	2.56	3.02	63.70	22.65
50-99	315	6.75	12.54	10.96	2.55	3.22	79.90	26.26
100-199	177	3.79	14.21	14.74	2.22	3.22	89.80	27.78
200-499	113	2.42	19.34	23.92	2.07	2.87	92.30	26.80
500+	35	0.75	18.26	24.11	1.79	1.92	99.40	27.64
TOTAL	4668	100.00	100.00	100.00	3.86	4.17	48.41	19.87

[a] All figures represent averages over the whole period 1994-2016.
[b] Shares and rates are given in %.
[c] Size group is given in terms of number of employees.

Table 2.3 reports the same average statistics, here, however, w.r.t. the different 4-digit woodworking sectors. The biggest sector in terms of number of firms is given by the sector sawmilling and planning of woods (1610), which contains about 19% of all firms, whereas the smallest sector is given by the manufacture of veneer sheets/wood-based panels/parquet floors (1621/22) and the manufacture of pulp and paper (1711/12), containing both only about 2% of all firms. In terms of turnover, the biggest sector is given by the manufacture of cardboard/packaging/etc. (1721/22), producing by about 25% of total turnover, whereas the smallest sector is represented by the manufacture for wooden containers (1629), given by somewhat less than 2% of total turnover. Table 2.3 also exhibits that entry and exit rates vary across sectors, ranging between 3.1% and 5.6%. The share of exporting firms varies considerably across sectors: For instance, the manufacture of pulp and paper (1711/12) reveals the highest share of exporting firms, given by about 83%. In contrast, the sector of other builders' carpentry and joinery (1623) shows a much lower share of exporters, given by only about 23%.

Table 2.3: Summary statistics w.r.t. 4-digit sectors: averages from 1994-2016[a,b]

Sector[c]	# of firms	Share of firms	Share of empl.	Share of turnover	Entry rate	Exit rate	Share of exporters	Age
1610	907	19.43	9.35	8.06	3.78	3.64	50.56	20.86
1621/22	95	2.04	4.12	5.15	3.21	3.49	68.76	22.06
1623	599	12.83	9.54	7.47	5.06	4.63	23.14	17.58
1624	493	10.56	6.97	5.65	3.48	3.46	50.91	20.10
1629	236	5.06	2.72	1.94	3.19	4.45	56.19	20.95
1711/12	110	2.36	11.12	20.14	3.64	3.76	83.14	21.59
1721/22	469	10.05	21.86	25.19	2.72	3.67	66.61	24.05
1723/24/29	302	6.47	7.51	7.67	2.84	3.14	68.58	22.34
3101	418	8.96	8.43	6.36	4.46	4.27	43.72	18.17
3102	208	4.46	4.65	3.60	3.90	3.64	29.02	17.18
3109	830	17.78	13.73	8.75	4.33	5.62	43.22	17.94
Total	4667	100.00	100.00	100.00	3.86	4.17	48.40	19.90

[a] All figures represent averages over the whole period 1994-2016.
[b] Shares and rates are given in %.
[c] 1610 - sawmilling/wood planning, 1621/22 - veneer sheets/wood-based panels/parquet floors, 1623 - other builders' carpentry/joinery, 1624 - wooden containers, 1629 - other products of wood, 1711/12 - pulp, paper, and paperboard, 1721/22 - cardboard/packaging/paper for domestic and health usage, 1723/24/29 - other products of paper, 3101 - office/shop furniture, 3102 kitchen furniture, 3109 - other furniture.

Moreover, Figure 2.1 presents the evolution of important aggregated variables, i.e. value added, labor and capital, as well as exports. The time series for each variable represent sums over all firms in the sample, normalized to 100 for the initial year 1994. The graph shows that the demand for capital, represented by the dashed line, has increased throughout the whole period, where the aggregate level in 2016 exceeds the level in 1994 by 45.7. Aggregate exports of the woodworking industry, given by the solid line, have increased until 2007, whereupon a sharp decrease took place - obviously related to the economic and financial crisis hitting the world economy at that time. From about 2009 on exports increase again, reaching a level of 133.4 w.r.t. 1994. Aggregate value added production, represented by the dotted line, has also increased until 2007 whereupon total value added consistently decreases. In 2016, the industry's total value added only accounts for 111.0 w.r.t. 1994. Lastly, aggregate labor (the number of workers over all firms), represented by the bottom line, shows the strongest negative trend, where in 2016 total labor only accounts for about 60.4 relativ

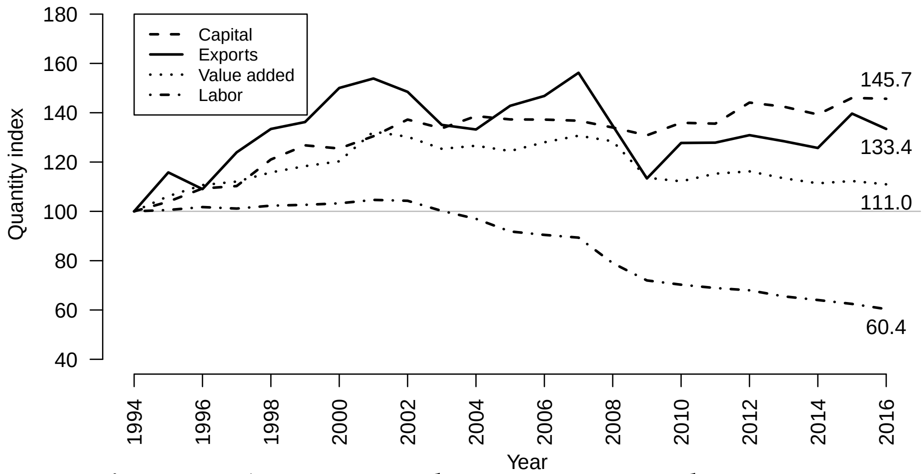

Figure 2.1: Aggregate production, exports, and inputs over time

Since firm entry and exit is a crucial aspect in this investigation, Figure 2.2 illustrates the evolution of the number of active firms and the corresponding entry and exit rate. The number of firms (with at least five employees), represented by the dashed line (with the corresponding values on the left y-axis), remains relatively stable until 2007/2008, whereupon a significant negative trend has taken place. In fact, in 2016 the number of active firms only accounts for about 70% w.r.t. 1994, which translates into a (negative) average annual growth rate of about -1.5%.[23] This trend is also reflected in the entry and exit patterns, represented by the solid and dotted lines (with the corresponding y-axis on the right), respectively. Until 2007/08 both the entry and exit rate oscillate at a similar level, whereas from 2008 on the exit rate lies consistently above the entry rate.

[22]See Appendix 2.10, Figure 2.8 for the evolution of aggregate value added, export, and inputs separately for each of the considered 4-digit sectors.

[23]See Appendix 2.10, Figure 2.9 for on changes in the number of firms w.r.t. the considered 4-digit sectors.

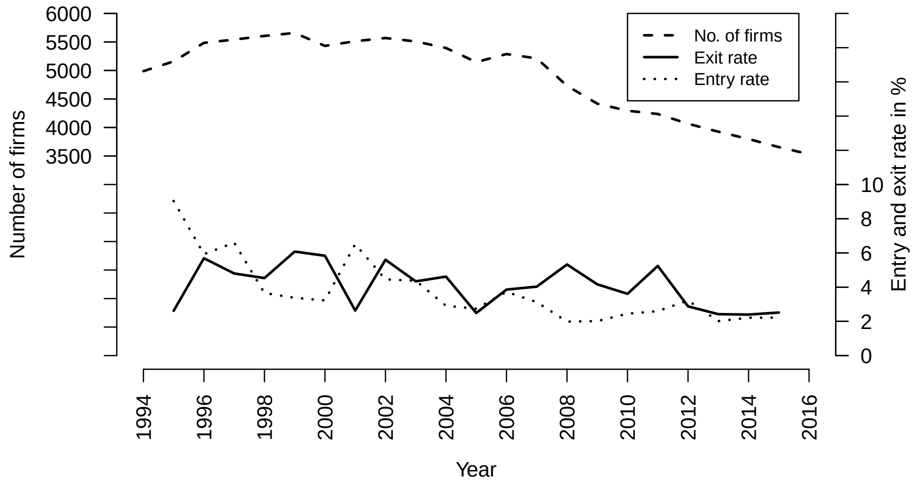

Figure 2.2: Number of firms as well as entry and exit rate over time

In this study, beside firm dynamics with entry and exit, firms' export behavior will be linked to aggregate productivity growth. To provide some basic information on the export behavior of firms active in the French woodworking industry Table 2.4 reports, for different periods, the share of exporters (columns 2) as well as the distribution of firms' share of exported production w.r.t. their total production (column 3-7). More precisely, the average share of exporters generally slightly increases from 48.1% for the period 1994-2000 to 50.8% for the period 2013-2016. Moreover, the share of firms' export sales w.r.t. their total sales also slightly increases over time. That is, while for the period 1994-2007 75% (99%) of all firms export 5.5% (77.5%) or less w.r.t. their total production, for the period 2013-2016 75% (99%) of all firms export 6.9% (84.8%) or less. This means that most of the firms in my sample produce mainly for the domestic market.

Table 2.4: Firms' export characteristics

Period	Share of exporters	Distribution of firms' exports w.r.t. their total production 50%	75%	90%	95%	99%
1994-2000	48.14	0.00	5.52	25.97	44.54	77.54
2001-2007	47.54	0.00	6.00	29.26	51.11	80.68
2009-2012	49.01	0.00	5.99	28.66	51.68	82.44
2013-2016	50.84	0.04	6.88	31.87	56.89	84.84

2.6 Empirical results of structural stability and productivity distribution

As earlier outlined in the chapter, I conduct the Wald-type test for structural stability for the two sub-periods, 1994-2007 and 2008-2016. Table 2.5 presents the empirical test results for structural, showing that for most of the 4-digit sectors the null hypothesis of structural stability is strongly rejected. More precisely, the only sector for which the null cannot be rejected is given by the manufacture of other builders' carpentry and joinery (1623), the manufacture of pulp and paper (1711/12) as well as the manufacture of kitchen furniture (3102). Generally, the test results give empirical support for structural instability between the two sub-periods and I therefore rely on the period specific parameter estimates in this study. That is, firm-level productivity is recovered based on the production function coefficients estimated from the two sub-periods. See Appendix 2.11.2 for the results of the estimates of the production function coefficients.

Table 2.5: Test for structural stability

	Sector*										
	1610	1621/22	1623	1624	1629	1711	1721/22	1723/24/29	3101	3102	3109
Statistic	254.277	8.496	3.576	9.009	6.296	3.474	33.162	34.181	198.003	3.067	213.741
p-value	0.000	0.014	0.167	0.011	0.043	0.176	0.000	0.000	0.000	0.216	0.000

* 1610 - sawmilling/wood planning, 1621/22 - veneer sheets/wood-based panels/parquet floors, 1623 - other builders' carpentry/joinery, 1624 - wooden containers, 1629 - other products of wood, 1711/12 - pulp, paper, and paperboard, 1721/22 - cardboard/packaging/paper for domestic and health usage, 1723/24/29 - other products of paper, 3101 - office/shop furniture, 3102 kitchen furniture, 3109 - other furniture.

Log TFP is computed based on the production function estimates. Figure 2.3 shows kernel density estimates of log firm-level productivity for the periods 1994-2007 and 2008-2016. The productivity distribution shifts to the right from the period 1994-2007 to 2008-2016, indicating a higher level of productivity for the latter period. This might be induces both due to the fact that I use for each sub-period different parameter estimates of the production function to recover firm-level productivity and by firms productivity improvements. The latter aspect will be examined in detail in the subsequent sections.

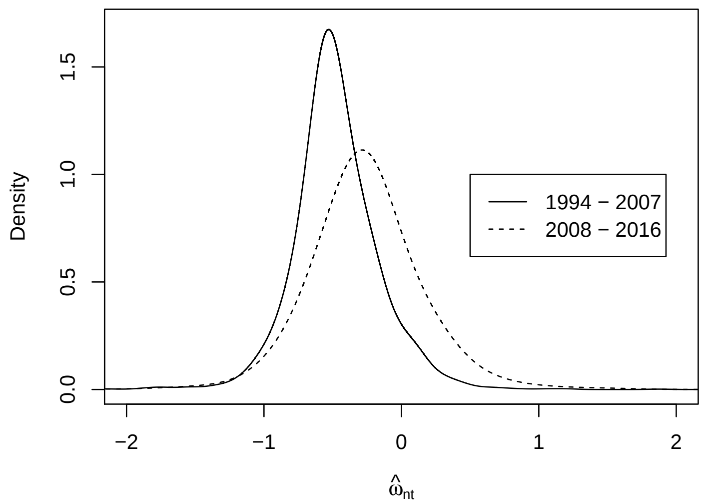

Figure 2.3: Kernel density estimates of log firm-level productivity

Table 2.6 shows some percentile ratios, corresponding to the two productivity distributions. The table suggests that productivity dispersion among firms has increased, as all ratios increase. I measure the most considerably change for the 99/1 percentile ratio, which is given for 1994-2007 and 2008-2016 by 5.56 and 9.40, respectively. That is, while over the period 1994-2007 the top 1% most productive firm was about five times more productive compared to the bottom 1% less productive firm, over the period 2008-2016, the most productive firms are about nine times more productive compared to the less productive firms. Cette et al. (2017) also finds an increase in the dispersion of productivity, considering firms active in the whole French economy. They highlight that an increase in productivity dispersion can be related to increasing inefficiency in the allocation of production factors, such as capital and labor.[24]

Table 2.6: Percentile ratios of the productivity distribution

Percentile ratio	1994-2007	2008-2016
90/10	2.04	2.45
95/5	2.71	3.38
99/1	5.46	9.40

[24] Also see Hsieh and Klenow (2009) and Restuccia and Rogerson (2013) for detailed discussion on that aspect.

2.7 Empirical results of aggregate productivity dynamics

This section presents the empirical results of aggregate productivity dynamics and its decomposition. In particular, Section 2.7.1 presents the results of the aggregate productivity decomposition with market entry and exit over all firms, Section 2.7.2 discusses differences of aggregate productivity dynamics w.r.t. firms' export status (e.g. exporter and non-exporter), and Section 2.7.3 illustrates the results of aggregate productivity dynamics related to firms' domestic and export economic activity.

2.7.1 Aggregate productivity with market entry and exit

Figure 2.4 shows the aggregate productivity level for the three firm groups, survivors, entrants and exitors, over all firms active in the French woodworking industry. The aggregate productivity of survivors, represented by the dashed line, increases especially until around 2008, whereupon it is difficult to graphically conclude for a significant change until 2015. The aggregate productivity level of the group of entrants and exitors, indicated by the solid and dotted line, respectively, is shown to be much more volatile and fluctuates around the level of aggregate productivity of the group of survivors. The figure suggests, though, that the aggregate productivity of both the groups of entrants and exitors follow the same trend compared to the aggregate productivity of the group of survivors, i.e. towards a higher level of productivity.[25]

[25]Note that according to the definition of firms' status of either survivor, entrant or exitor, described in Section 2.4.2, 1995 and 2015 are the first and the last years at which the status can be identified. Also see Appendix 2.13.1, Table 2.19 providing more details on yearly aggregate productivity and sales shares w.r.t. the different firm groups.

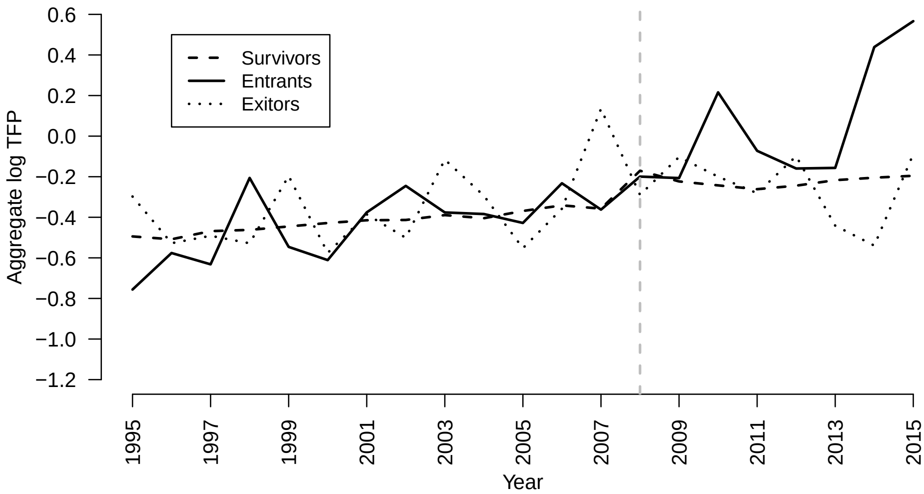

Figure 2.4: Aggregate productivity levels of the groups survivors, entrants, and exitors (over all firms)

Figure 2.5 illustrates the corresponding total annual growth rates of aggregate productivity, as well as the contributions related to the three firm groups, survivors, entrants, and exitors. The contributions of the different groups to aggregate productivity growth are calculated according to the DOPD decomposition presented in Section 2.3.2.[26] The graph shows that total growth, represented by the solid line, is, except for few years, mostly positive and closely followed by the contribution of the group of survivors. This is not surprising since each group's contribution to aggregate productivity growth is weighted by its aggregate sales share, where surviving firms detain by far the largest sales share.[27] It follows that, the contribution of the group of entrants and exitors to the aggregate productivity growth, represented by the dotted and dashed-dotted lines, respectively, are much lower compared to the contribution of survivors and are, hence, always very close to the zero line. The large productivity growth rate in 2008 (given by the peak of total growth and the contribution of survivors) is related to the structural instability between the two period 1994-2007 and 2008-2016. More specifically, by the change in the production function parameters, I measure for 2008, the year of structural break (indicated by the vertical dashed line), a high growth rate in aggregate productivity, induced by a higher productivity level of the group of surviving firms.[28]

[26]Since 1995 is the first year at which survivors, entrants, and exitors can be identified, the first year of aggregate productivity growth (and its contributors) can be measured only at 1996. The last year at which growth rates can be measured is given by 2015.

[27]See Appendix 2.13.1, Table 2.19.

[28]This can also be seen in Figure 2.4, where the productivity level of the group of surviving firms increases considerably from 2007 to 2008.

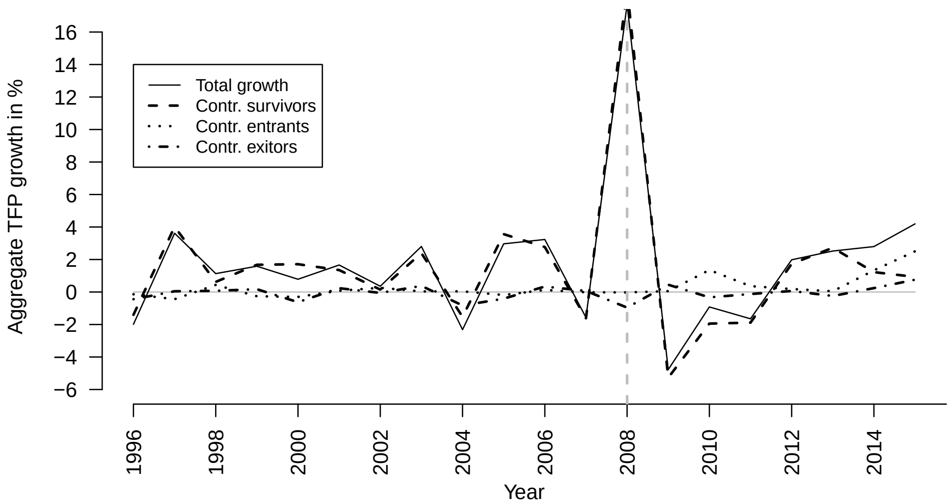

Figure 2.5: Aggregate productivity growth (DOPD, over all firms)

In order to more accurately investigate aggregate productivity growth, Table 2.7 presents the decomposition results for the sub-periods 1994-2000, 2001-2007, 2008-2012, and 2012-2013. The latter two sub-periods are chosen to investigate aggregate productivity growth during and after the economic crisis, which started towards the end of 2007. The table reports total aggregate productivity growth rates over all firms, annual average productivity growth rates (given in parenthesis) as well as the respective contributions of the groups of survivors, entrants, and exitors.[29] Also, the contribution of survivors is further decomposed into the within and between growth contribution.

Consider first the total (annual average) growth, given in the second column. Aggregate productivity growth is higher during the first two periods 1994-2000 and 2001-2007, given by 7.97% with an annual average of 1.29% and 6.69% (1.09%), compared to the last two periods, 2008-2012 and 2012-2016. During the financial and economic crisis, 2008-2012, I measure a considerable negative productivity growth, here given by only -5.87% (-1.44%). Over the last period, instead, aggregate productivity growth recovers, with a total (annual average) growth rate, given by 3.73% (1.23%). A productivity slowdown from 2000 on is also found by Cette et al. (2017), investigating the whole French economy, and by De Monte (2021), studying the French manufacturing industry. This suggests that the here presented findings are not only a characteristic specific to the woodworking industry but also reflect general patterns of the French economy. Splitting up the total growth into its different contributors it can be seen that the group of surviving firms is an important driver for aggregate productivity growth. Here, especially during the first two periods, the group of surviving

[29] Note that here firms' status of either survivor, entrant or exitor determined according to the definition of entry and exit over longer time spans, see Section 2.4.2.

firms contributes considerably through the within productivity growth contribution (learning effect), given for 1994-2001 and 2001-2007 by 7.95% (1.28%) and 5.99% (0.97%), respectively. Surviving firms' contribution to aggregate productivity growth through sales shares reallocation (between contribution) is found to be less. Remarkably, for the crisis period, 2008-2012, I measure a stark negative within and between growth rate, given by -3.26% (-0.80%) and -2.68 (-0.66)%. Finally, over the last period, 2013-2016, surviving firms' within contribution remains negative, while their between contribution, induced by the reallocation process of sales shares, becomes positive again.

Table 2.7: Aggregate productivity growth (DOPD) over all firms[a]

Period	Total Growth[b]	Contribution Survivors Within	Between	Contribution Entrants	Contribution Exitors
1994 - 2000	7.97 (1.29)	7.95 (1.28)	2.11 (0.35)	-1.36 (-0.23)	-0.73 (-0.12)
2001 - 2007	6.69 (1.09)	5.99 (0.97)	0.55 (0.09)	0.43 (0.07)	-0.28 (-0.05)
2008 - 2012	-5.87 (-1.44)	-3.26 (-0.80)	-2.68 (-0.66)	0.59 (0.15)	-0.52 (-0.13)
2013 - 2016	3.73 (1.23)	-2.68 (-0.88)	5.36 (1.76)	-0.25 (-0.08)	1.29 (0.43)

[a] All figures represent growth rates in % relative to the initial year of the given period. Average annual growth rates are given in parenthesis.

[b] The total growth in aggregate productivity is the sum of the contributions of survivors, entrants and exitors.

Haltiwanger (2011) describes that both positive within and between contribution points to a "well working" economy from a welfare perspective, since the economy is able to produce a given output at less costs. That is, positive within growth rates reflects firms' ability to improve their productivity through learning while positive between contribution indicates a higher level of allocative efficiency as sales shares shift from less to more productive firms. The general picture indicates that surviving firms manage to improve their productivity until 2007 whereupon they encounter considerable difficulties in continuing that trajectory. Further, by mostly positive between contributions, the woodworking industry exhibits improvements in allocative efficiency.

Consider now in Table 2.7 the contribution of aggregate productivity growth of the firm groups of entrants and exitors. Generally, I find that the contribution of both firm groups is less compared to the one of survivors, with changing sign for their contribution. This finding goes largely in line with other similar studies (Baily et al., 1992; Foster et al., 2001; Melitz and Polanec, 2015; Ben Hassine, 2019; De Monte, 2021). According to the DOPD approach, if entering (exiting) firms' contribution is positive, their aggregates productivity is larger (smaller) compared to the group of surviving firms. Here, especially the group of exiting firms shows for the most periods a negative contribution, which indicates that the industry has lost relatively productive firms.

The DOPD presented in Table 2.8, splits aggregate productivity and sales shares measures w.r.t. the three firm groups. More precisely, the table is separated into two panels:

Panel A reporting measures in the initial year of the period (Year 1), i.e. aggregate productivity and sales shares of those firms that survive and exit until/before the last year of the period; And Panel B, reporting the measures at the last year of the period (Year 2), i.e. aggregate productivity/output shares of those firms that have survived/entered until the last year.[30] Table 2.8 also provides some insights into the allocation of sales shares between the groups of survivors and exitors, given in Panel A (measured at Year 1 of a given period) as well as the allocation of sales shares for the groups of survivors and entrants, given in Panel B (measured at Year 2 of a given period). It can be seen that group of survivors always detains by far the largest aggregate sales share, given by at least 80%. This is important to notice since, according to the employed aggregate productivity decomposition, each group's aggregate productivity is weighted by its aggregate sales share and thus highlights why surviving firms contribute considerably more compared to entering and exiting firms.

Table 2.8: Aggregate productivity and sales shares[a]

Panel A: Measures at Year 1							
Year 1	Year 2	$\Omega_{S,1}$	$S_{S,1}$	$\Omega_{X,1}$	$S_{X,1}$	No. Surv.	No. Exitors
1994	2000	-0.532	85.70	-0.481	14.30	3265	726
2001	2007	-0.421	80.12	-0.407	19.88	3526	978
2008	2012	-0.173	87.03	-0.133	12.97	3033	654
2013	2016	-0.188	94.33	-0.416	5.67	2934	248
Panel B: Measures at Year 2							
Year 1	Year 2	$\Omega_{S,2}$	$S_{S,2}$	$\Omega_{E,2}$	$S_{E,2}$	No. Surv.	No. Entrants
1994	2000	-0.432	83.71	-0.515	16.29	3265	1096
2001	2007	-0.356	87.47	-0.321	12.53	3526	811
2008	2012	-0.233	90.20	-0.173	9.80	3033	325
2013	2016	-0.161	94.02	-0.203	5.98	2934	128

[a] The columns $\Omega_{G,j}$ and $S_{G,j}$ with $G = \{S, X, E\}$ and $j = \{1, 2\}$, denote the aggregate productivity and the aggregate sales share of the firm groups survivors, exitors, and entrants - measured for the initial year (Year 1) and the last year of the period (Year 2). All sales shares $S_{G,j}$ are given in %.

2.7.2 Aggregate productivity and export status

To relate aggregate productivity growth with firms' export status, I apply the DOPD approach separately on the group of non-exporter and exporter. Table 2.9 presents the results. The figures represent growth rates (average annual growth rates in parenthesis) within the two group of firms, taking market entry and exit into account. The column "total growth" shows that non-exporting firms reveal a relatively higher growth rate for the two initial periods compared to the group of exporting firms. More specifically, for 1994-2000 and 2001-2007, non-exporting (exporting) firms increase their productivity by 9.41% (8.12%) and

[30]Note that Table 2.7 corresponds to equation (2.11), whereas Panel A and Panel B in Table 2.8 correspond to equation (2.9) and (2.10), respectively.

11.16% (6.13%). Instead, for the last two periods non-exporting firms encounter more difficulties to keep improving their productivity compared to exporting firms. That is, for 2009-2012 and 2013-2016, total aggregate productivity growth of non-exporting (exporting) firms is given by -8.28% (1.25%) and 1.20% (3.79%). As the table also shows, exporting firms were able to increase their aggregate productivity by a sustainable positive within contribution over the last two periods. Instead, the negative within contribution of the group of non-exporters has considerably reduced their aggregate productivity growth.[31,32] The figures suggest, hence, that aggregate productivity growth of the group of exporting firms is more consistent and more resilient during times of economic distress compared to the aggregate productivity growth of non-exporters. This is intuitive for two reasons: First, beside the export activities, exporting firms tend to detain higher sales shares in the domestic market; Second, since exporting firms may be able to compensate losses in terms of sales and sales shares in the domestic market by their export activity. The results confirm Harris and Li (2008) who provide evidence that exporting firms in the UK economy (1994-2004) contribute more to aggregate productivity growth compared to non-exporting firms.

Table 2.9: Aggregate productivity growth (DOPD) by firms' export status[a]

Export status	Period	Total growth[b]	Contribution survivors Within	Contribution survivors Between	Contribution entrants	Contribution exitors
Non-exporter	1994 - 2000	9.41 (1.51)	8.53 (1.37)	0.95 (0.16)	0.03 (0.01)	-0.11 (-0.02)
	2001 - 2007	11.16 (1.78)	5.46 (0.89)	5.92 (0.96)	0.04 (0.01)	-0.25 (-0.04)
	2009 - 2012	-8.28 (-2.69)	-2.95 (-0.97)	-5.59 (-1.83)	0.17 (0.06)	0.08 (0.03)
	2013 - 2016	1.20 (0.40)	-6.92 (-2.25)	7.98 (2.59)	0.14 (0.05)	0.00 (0.00)
Exporter	1994 - 2000	8.12 (1.31)	7.00 (1.13)	3.10 (0.51)	-1.36 (-0.23)	-0.62 (-0.10)
	2001 - 2007	6.13 (1.00)	6.31 (1.03)	-0.49 (-0.08)	0.33 (0.05)	-0.03 (0.00)
	2009 - 2012	1.25 (0.41)	1.77 (0.59)	-0.53 (-0.18)	0.39 (0.13)	-0.37 (-0.12)
	2013 - 2016	3.79 (1.25)	0.58 (0.19)	2.36 (0.78)	-0.44 (-0.15)	1.29 (0.43)

[a] All figures represent growth rates in % relative to the initial year of the given period. Average annual growth rates are given in parenthesis.
[b] The total growth in aggregate productivity is the sum of the contributions of survivors, entrants and exitors.

In order to compare the individual productivity levels of the two groups of non-exporting and exporting firms, I apply the concept of first-order stochastic dominance. This is done by graphically comparing the empirical cumulative distribution function (ECDF) as well as by the conduction of the Kolmogorov-Smirnov (KS) test (Kolmogorov, 1933; Smirnov, 1939) to assess statistical significance in the difference between both distributions.[33] The intuition is that if, for instance, the productivity ECDF belonging to the group of exporting firms is consistently located to the right w.r.t. the ECDF of non-exporting firms, then exporters have

[31] Similarly to the case where the DOPD approach was applied to all firms, irrespective to their export status, here firm entry and exit plays a minor role to aggregate productivity change, too.
[32] Also see Appendix 2.13.3, Table 2.23, for detailed information on both aggregate sales shares and aggregate productivity of the different firm groups.
[33] See Appendix 2.13.3 for a detailed description of the approach.

a higher productivity level at any percentile of the productivity distribution. Figure 2.6 illustrates for the investigated sup-periods the comparison of the ECDFs belonging to the two groups of firms. It can be seen that for all periods, the productivity ECDF of exporting firms is located to the right compared to the ECDF of non-exporting firms, implying, hence, higher productivity levels of exporters over to whole range of the productivity distribution.

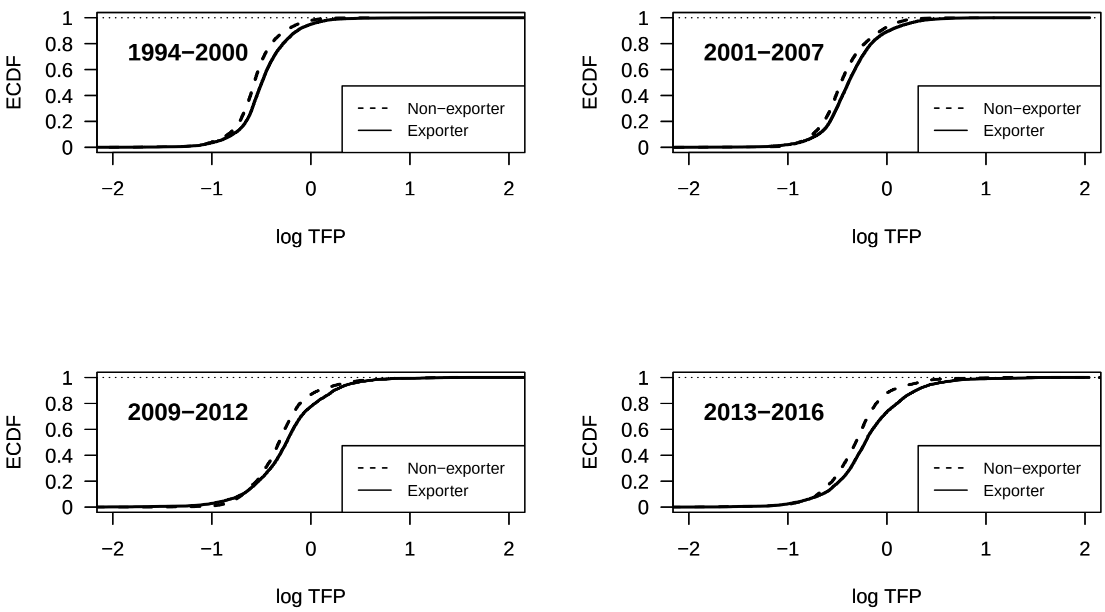

Figure 2.6: Comparing the productivity distribution of domestic and exporting firms

Complementary, Table 2.10 presents the KS-test results. The table shows that the two sided test, testing for equality of both distributions, is highly rejected for all periods, meaning that the productivity distribution of exporters and non-exporters firms do not follow the same distribution. Further, the one-sided test, testing the null hypothesis of a difference in productivity favorable to exporters, is, except for 2009-2012, highly rejected. This suggest that exporters are significantly more productive compared to firms only active on the domestic market. Also, the last column of Table 2.10 illustrates that the median TFP level of exporters exceeds the median TFP level of non-exporters between 7.49% (1994-2000) and 9.54% (2013-2016). The finding of higher productivity of exporters goes in line with literature that mostly documents productivity advantages for exporting firms (Bernard and Jensen, 1999; Harris and Li, 2008; Bellone et al., 2014; De Loecker, 2013).

Table 2.10: KS-test for first-order stochastic dominance between exporting and non-exporting firms

Period	Observations: # of exporter	Observations: # of non-exporter	Two-sided test H_0: Equality of distributions: Statistic	Two-sided test H_0: Equality of distributions: p-value	One-sided test H_0: Difference favorable to exporters: Statistic	One-sided test H_0: Difference favorable to exporters: p-value	Median TFP difference
1994-2000	9890	6924	0.169	0.000	0.002	0.977	7.49%
2001-2007	10436	8823	0.132	0.000	0.008	0.564	7.54%
2009-2012	5567	4921	0.128	0.000	0.025	0.040	7.46%
2013-2016	5167	4348	0.164	0.000	0.007	0.816	9.54%

2.7.3 Aggregate productivity and domestic and export activity

An important feature of the French woodworking industry is that about 75% of total production is distributed on the domestic market, i.e., most firms only export very little w.r.t. their total sales.[34] For this reasons it seems important to relate aggregate productivity growth not only to firms' export status, but also their volumes of sales in the domestic and export market. Section 2.3.2 presented the aggregate productivity decomposition for this purpose. Remember that I here simply split firms' sales shares into its domestic and export component, respectively. I then apply the static Olley-Pakes productivity decomposition to continuing firms, i.e., without taking market entry and exit effects into account that are studied in the previous sections. In this manner I am able to investigate, to which extend productivity growth dynamics are related to the domestic and export economic activity.

Table 2.11 presents the corresponding the results. The table shows that especially during the first two periods, 1994-2000 and 2001-2007, total growth is mainly driven by firms' domestic activity. For instance, considering the period 1994-2000, the contribution to aggregate productivity growth of firms' domestic activity is given by 7.2% (sum of within and between contribution) whereas aggregate productivity growth from firms' export activity is only given by 2.16%. Here, in particular, firms' within growth related to domestic activity contributes considerably to the aggregate productivity growth. A similar pattern is measured for the period 2001-2007. For the period of economic distress, 2009-2012, as well as for 2013-2016, the within contribution related to both domestic and export activity is measured to be negative. Here, compared to the first two periods, especially the within contribution related to domestic activity reduces dramatically, given by -0.22% and -1.86%, respectively. Over the last period, I measure a considerable positive between contribution related to both firms' domestic and export activity, indicating that after the crisis, domestic and export sales shares were considerably reallocated from less to more productive firms.

[34] See Section 2.5, Table 2.4, and Appendix 2.13.3, Table 2.24.

Table 2.11: Olley-Pakes productivity decomposition w.r.t. firms' domestic and export activity

Period	Total growth	Domestic activity Within	Domestic activity Between	Export activity Within	Export activity Between
1994 - 2000	9.36 (1.50)	6.82 (1.11)	0.38 (0.06)	1.13 (0.19)	1.03 (0.17)
2001 - 2007	7.56 (1.22)	4.09 (0.67)	0.42 (0.07)	1.89 (0.31)	1.15 (0.19)
2009 - 2012	-0.56 (-0.19)	-0.22 (-0.07)	0.16 (0.05)	-0.35 (-0.12)	-0.16 (-0.05)
2013 - 2016	3.37 (1.11)	-1.86 (-0.62)	3.74 (1.23)	-0.81 (-0.27)	2.31 (0.76)

[a] All figures represent growth rates in % relative to the initial year of the given period. Average annual growth rates are given in parenthesis.

[b] The total growth in aggregate productivity is the sum of the contributions of survivors, entrants and exitors.

The key message from this section is that firms domestic activity is a crucial driver for aggregate productivity growth, which is induced by the high share of sales distributed in the domestic market. That is, while exporting firms exhibit higher productivity levels and a more sustainable aggregate productivity growth, domestic economic activity states the most important pillar for the industry's productivity growth. Generally, my results suggest that a higher degree of internationalization of the French woodworking industry could have two positive effects. Fist, more firms would benefit from export-learning increasing their individual productivity (Bellone et al., 2008). Second, by higher export sales shares aggregate productivity would be less vulnerable to domestic economic distress, thus, allowing for a more sustainable aggregate productivity and economic growth.

2.8 Conclusion

This chapter investigates productivity dynamics in the French woodworking industry between 1994 and 2016. More specifically, it analyses the effect of market entry and exit on aggregate productivity growth as well as the relation between firms' export status (i.e. exporting or non-exporting) and export volumes and aggregate productivity growth in the industry. For this purpose I use French firm-level data covering the period from 1994-2016 and estimate firm-level productivity based on a value added Cobb-Douglas production function, following Ackerberg et al. (2015).

Compared to more recent periods, I find that the industry's total aggregate productivity growth is considerably higher for the periods 1994-2000 and 2001-2007. During the period of worldwide economic distress, 2008-2012, a remarkable slowdown in productivity growth took place, with some improvement during the period after the economic crisis, 2012-2016, which goes in line with other studies considering productivity of the French economy (Cette et al., 2017; Ben Hassine, 2019; De Monte, 2021). The analysis further shows that an important driver for these dynamics is the contribution of the group of incumbent firms, where market entry and exit reveals a much lower contribution. Moreover, investigating aggregate productivity growth separately w.r.t. firms export status, i.e. non-exporting and exporting firms, I find that the group of exporting firms feature higher aggregate productivity growth rates compared to the group of non-exporting firms. This result is similar to the findings by Harris and Li (2008), who investigate UK firms. Further, applying the concept of first order stochastic dominance, exporter show higher productivity levels on the whole range of the productivity distribution, where I measure exporters' median productivity as 7% and 9% higher compared to non-exporters. However, when decomposing aggregate productivity into the part contributed by firms' domestic and export activity, the results suggest, that domestic activity contributes considerably more to aggregate productivity growth for the periods 1994-2000 and 2001-2007, compared to the contribution of export activity. This is due to the fact that by far the largest part of firms' production is for the domestic market. That is, the slowed aggregate productivity growth is mainly transmitted by firms' domestic activity. Therefore, given firms learn and improve through exporting (Bellone et al., 2008; De Loecker, 2013), my results suggest that a more international orientation of the French woodworking industry promotes a higher and more sustainable aggregate productivity growth, which would, in turn, also be more resilient to domestic economic distress. Moreover, as the French woodworking industry exhibits a considerable trade deficit (Levet et al., 2014), losing sales share on the global market (Koebel et al., 2016), further research should be done to better understand the barriers preventing firms from engaging in export activity and to evaluate what policy measures would be best suited to support firms' competitiveness in the global market.

The analysis performed in the chapter leaves room for improvement in several ways. First, the use of a value added Cobb-Douglas production function, implying constant output elasticities across firms, is restrictive. More general models, such as a translog production technology (De Monte, 2021; De Loecker and Warzynski, 2012) and/or nonparametric estimation approaches of production functions (Demirer, 2020; Doraszelski and Jaumandreu, 2018), would allow for more flexibility. Second, firm productivity is estimated from revenue data and as such it conflates price-setting effects with physical productivity. In other words, a firm might be considered productive as it is cost-effective or because it has significant market power. Using firm-level price indicators (Morlacco, 2017) or physical output/input data would be possible ways to avoid this issue. Third, the measure of market entry and exit is only based on firm observations in the data but not on the legal activity status of a firm, which might bias the effect of firm entry and exit on aggregate productivity.

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2.9 Appendix A: Data

2.9.1 Merging of the data sets FICUS and FARE

For the analysis the two fiscal firm-level data sets FICUS and FARE are merged, covering the periods from 1994 to 2007, and 2008 to 2016, respectively. Both in FICUS and FARE firms are classified by a 4-digit sector nomenclature "NAF" (nomenclature d'activité française). However, from 2008 onward, the FARE sectoral nomenclature changed: new sectors appeared (some FICUS sectors were split), some FICUS sectors disappeared (were merged into a FARE sector). In FICUS, the nomenclature was organized according to "NAF 1", while in FARE the nomenclature is organized according to "NAF 2". In this study a single data set is constructed, 1994 - 2016, by extending the sector nomenclature NAF 2 throughout the whole period. That is, the current 4-digit sector nomenclature NAF 2 are assigned retrospectively to all firms observed in FICUS. For firms that are observed both in FICUS and FARE or only in FARE their 4-digit sector according to NAF 2 is known. However, for firms that have exited the market before 2008 we do not know to which NAF 2 4-digit sector they would have belonged to if they had continued their activity. To also classify these firms by the NAF 2 4-digit nomenclature the following methodology is used: First only those firms that are observed in both data sets, FICUS and FARE, are considered. From these observations a transition matrix is built where each row represents a 4-digit sector according to NAF 1 and each column represents a 4-digit sector according to NAF 2. Each cell of the transition matrix contains the number of firms transiting from a specific 4-digit sector in FICUS (NAF 1) to the new 4-digit sector in FARE (NAF 2). Table 2.12 shows an exemplifying transition matrix, choosing the NAF 1 4-digit sectors 201A - 205C, i.e. the manufacture of wood and products of wood. For instance, it can be seen that there are 2060 firms observed that were classified in FICUS in 201A (first row) and in FARE in the sector 1610 (third column), while there are only 46 observations that were classified in 201A and in FICUS in 0220 (first column). From these observed transition frequencies the transition probabilities are then calculated by simply dividing each element of the matrix by the sum of its corresponding row. That is, the NAF 1 - NAF 2 transition probabilities are calculated by

$$p_{IJ} = \frac{\sum_{n \in I,J}^{N_J} \mathbf{1}_{[n \in I \text{ and } n \in J]}}{\sum_{n \in I}^{N_I} \mathbf{1}_{[n \in I]}}, \tag{2.15}$$

where n is a firm observed in both FICUS and FARE, I and J are specific 4-digit sectors according to NAF 1 and NAF 2, respectively. **1** is an index variable equal to 1 if the condition in parenthesis is fulfilled. Table 2.13 contains the transition probabilities according to the observed transitions Table 2.12. It can be seen that those 4-digit transitions between FICUS and FARE that were more frequently observed obtain accordingly higher probabilities. In a second step, firms only observed in FICUS belonging to a specific NAF 1 4-digit sector, are assigned to a NAF 2 (at the 4-digit level), by a random draw with transition probabilities given the row of Table 2.13.

Table 2.12: FICUS - FARE: Observed transition frequencies

	NAF 2																		
NAF 1	0220	1392	1610	1621	1622	1623	1624	1629	2223	2512	3101	3109	3319	4329	4332	4391	4399	5610	9524	Total
201A	46	0	2060	5	6	22	35	12	0	0	0	7	0	0	25	24	9	5	0	2256
201B	0	0	498	0	0	0	0	0	0	0	0	0	0	17	4	36	24	0	0	579
202Z	0	0	0	108	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	112
203Z	0	7	33	0	15	1880	8	8	41	26	0	41	0	6	1005	386	34	0	0	3490
204Z	0	0	17	0	0	4	857	6	0	0	0	0	35	0	6	0	0	0	0	925
205A	4	16	10	4	0	21	5	1215	0	0	12	317	0	0	87	0	4	10	156	1861
205C	0	0	0	0	0	0	0	86	0	0	0	0	0	0	0	0	0	0	0	86

Table 2.13: FICUS - FARE: Transitions probabilities

	NAF 2																		
NAF 1	0220	1392	1610	1621	1622	1623	1624	1629	2223	2512	3101	3109	3319	4329	4332	4391	4399	5610	9524	Total
201A	0.02	0.00	0.91	0.00	0.00	0.01	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	1.00
201B	0.00	0.00	0.86	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.01	0.06	0.04	0.00	0.00	1.00
202Z	0.00	0.00	0.00	0.96	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	1.00
203Z	0.00	0.00	0.01	0.00	0.00	0.54	0.00	0.00	0.01	0.01	0.00	0.01	0.00	0.00	0.29	0.11	0.01	0.00	0.00	1.00
204Z	0.00	0.00	0.02	0.00	0.00	0.00	0.93	0.01	0.00	0.00	0.00	0.00	0.04	0.00	0.01	0.00	0.00	0.00	0.00	1.00
205A	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.65	0.00	0.00	0.01	0.17	0.00	0.00	0.05	0.00	0.00	0.01	0.08	1.00
205C	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00

2.9.2 Data cleaning

Table 2.14 provides information about the raw data, i.e., without any data cleaning. The motivation of the table is to show observations irrespective of number of workers, and/or missing, zero, and negative values for value-added, capital and materials. The table shows that in the raw data, the share of firms with less than five employees accounts for about 56%. These firms, however, only account for about 4.8% of total turnover. That is, firms with five and more employees represent approximately about 95% of total turnover.

Table 2.14: Summary statistics w.r.t. firm size, all observations[a,b]

Size group[c]	# of firms	Share of firms	Share of empl.	Share of turnover	Entry rate	Exit rate	Share of exporter	Age
0	6370	29.44	0.06	1.32	11.09	10.83	3.44	12.05
1	2606	12.05	1.33	0.92	7.76	8.15	6.96	13.13
2-4	3127	14.45	4.34	2.52	6.75	7.02	13.47	13.91
5-9	2115	9.78	7.14	4.46	5.48	5.66	27.73	16.01
10-19	1362	6.30	9.35	6.63	4.35	5.13	45.17	19.22
20-49	1192	5.51	18.68	14.88	2.82	3.61	63.33	22.51
50-99	335	1.55	11.64	10.23	2.72	3.90	79.75	26.24
100-199	187	0.86	13.06	13.54	2.52	3.93	89.18	27.77
200-499	120	0.55	17.86	22.17	2.33	3.54	91.71	27.16
500+	37	0.17	16.56	22.57	2.08	2.20	98.84	27.41
NA	4183	19.34	0.00	0.75	15.09	11.90	9.03	12.99
Total	21634	100.00	100.00	100.00	9.14	8.68	17.27	14.51

[a] All figures represent averages over the whole period 1994-2016.
[b] Shares and rates are given in %.
[c] Size group is given in terms of number of employees. NA denotes the group of firms for which the number of employees is not available.

2.10 Appendix B: Descriptive statistics

2.10.1 Share of the French woodworking industry w.r.t. the overall manufacturing industry

Table 2.15 provides some quantitative information mentioned in the introduction, concerning the importance of the woodworking industry w.r.t. the overall French manufacturing industry. The table is based on the sample without any restriction on observations in terms of firm size or other variables and figures are calculated for the whole period 1994-2016. The table shows that the share of firms active in the woodworking industry accounts for about 10%, w.r.t. all firms active in the French manufacturing. Further, the woodworking industry's share of turnover and exports is given by 4.6% and 3.2%, respectively. As also mentioned in the main text, these shares are however decreasing over time, as can be seen in Figure 2.7, illustrating the share of the French woodworking industry in terms of the number of firms, workers, turnover, and exports w.r.t. the overall manufacturing industry. All shares show a decreasing tendency over time, indicating a lower economic importance of the woodworking industry.

Table 2.15: Share of the French woodworking industry w.r.t. overall manufacturing industry[a]

Manufacturing	No. of firms	Share of firms	Share of employees	Share of turnover	Share of exports
Woodworking[b]	5351	10.05	7.02	4.62	3.19
Other[c]	47889	89.95	92.98	95.38	96.81

[a] Shares are given in %.
[b] Contains firms with at least than 5 employees belonging to those 4-digit woodworking sectors considered in this chapter.
[c] Contains firms with at least than 5 belonging to all other manufacturing industries (2-digit nomenclature 10-33, NAF, révision 2, 2008).

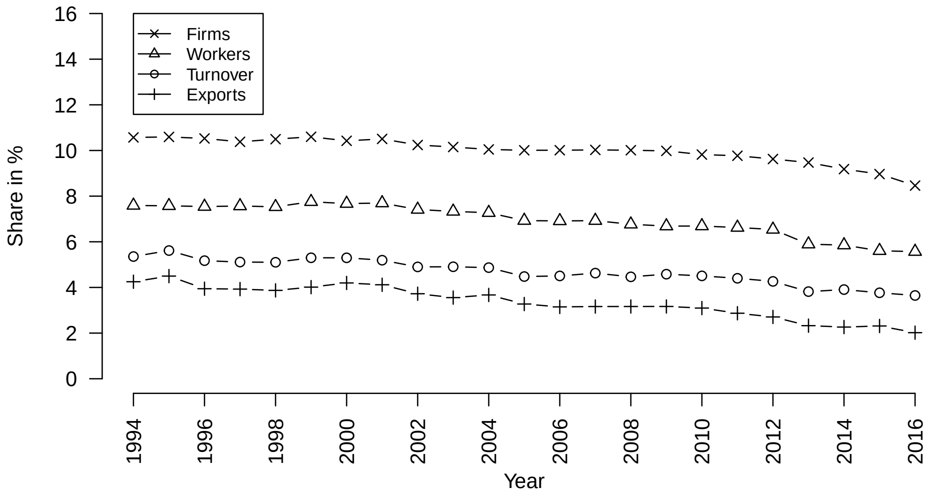

Figure 2.7: Shares over time of the French woodworking industry w.r.t. the overall French manufacturing

2.10.2 Evolution of value added, inputs, and exports by 4-digit sectors

Complementary to Figure 2.1 in the main text, Figure 2.8 shows production variables and exports over time for the different woodworking 4-digit sectors. The illustrated variables are aggregates over all firms active in the specific industry and year. The y-axis shows the values of a quantity index, where the initial year 1994 represents 100 for each of the evolving variables, capital, exports, value added and labor demand.

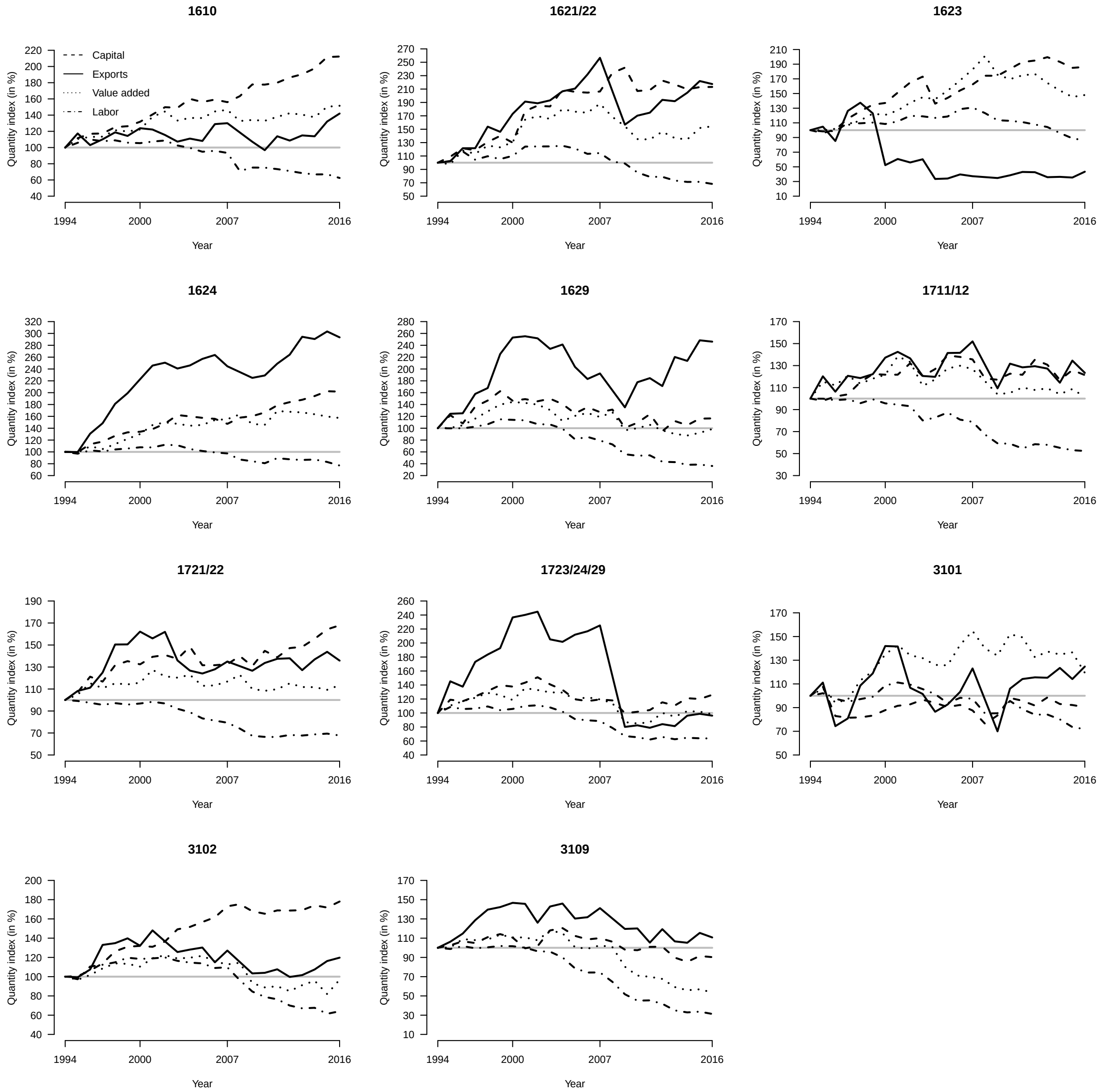

Figure 2.8: The evolution of aggregate value added, exports, and inputs for all included 4-digit woodworking sectors
1610 - sawmilling/wood planning, 1621/22 - veneer sheets/wood-based panels/parquet floors, 1623 - other builders' carpentry/joinery, 1624 - wooden containers, 1629 - other products of wood, 1711/12 - pulp, paper, and paperboard, 1721/22 - cardboard/packaging/paper for domestic and health usage, 1723/24/29 - other products of paper, 3101 - office/shop furniture, 3102 kitchen furniture, 3109 - other furniture.

Complementary to Figure 2.2 in the main text, Figure 2.9 shows the evolution of the number of firms, expressed in percent, for all included 4-digit woodworking sectors. Here, the initial year of the sample, 1994, represents the base year, given by 100%. The figure shows that all sectors, at least from 2007/2008 on, show a negative trend in the number of active firms.

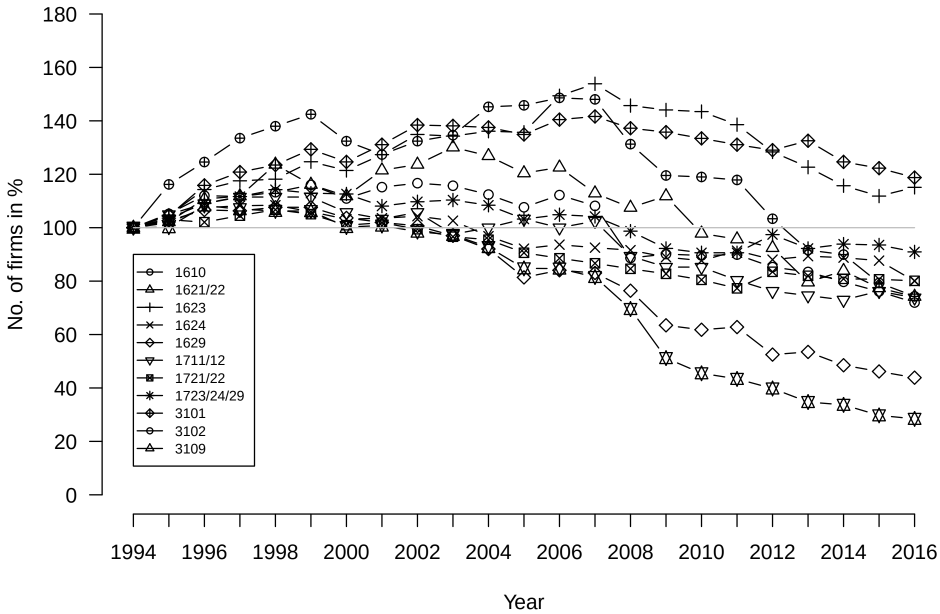

Figure 2.9: Evolution of number of active firms in %

1610 - sawmilling/wood planning, 1621/22 - veneer sheets/wood-based panels/parquet floors, 1623 - other builders' carpentry/joinery, 1624 - wooden containers, (1629) other products of wood, 1711/12 - pulp, paper, and paperboard, 1721/22 - cardboard/packaging/paper for domestic and health usage, 1723/24/29 - other products of paper, 3101 - office/shop furniture, 3102 kitchen furniture, (3109) other furniture.

2.11 Appendix C: Production function estimation

This section presents more details on the estimation and the results of the Cobb-Douglas value added production function. In particular, Section 2.11.1 provides a chunk code of the estimation procedure using the statistical software R, Section 2.11.2 presents the estimation results of the production function parameters, and Section 2.11.3 illustrates the distribution of the production function residual from the first stage estimation.

2.11.1 Chunk code

Recall, I estimate the production function by making use of the proxy variable approach, presented by Olley and Pakes (1996) and closely follow Ackerberg et al. (2015). The production function to be estimated is given by

$$q_{nt} = \beta_L l_{nt} + \beta_K k_{nt} + \omega_{nt} + \epsilon_{nt},$$

where I keep the same notation as in the main text. The first stage of the estimator consists in a nonparametric estimation of the term $\Phi(l_{nt}, k_{nt}, m_{nt}, \mathbf{c}_{nt})$, derived from

$$\begin{aligned} q_{nt} &= \beta_L l_{nt} + \beta_K k_{nt} + \tilde{h}_t^{-1}(k_{nt}, l_{nt}, m_{nt}, \mathbf{c}_{nt}) + \epsilon_{nt} \\ &= \Phi(l_{nt}, k_{nt}, m_{nt}, \mathbf{c}_{nt}) + \epsilon_{nt}. \end{aligned}$$

I use the statistical software R and estimate $\Phi(\cdot)$ nonparmaterically, by making use of kernel regression techniques, implemented in the **np** package (Hayfield and Racine, 2015). Optimal bandwidths are obtained by using the expected Kullback-Leibler cross-validation method (Hurvich et al., 1998). In the second step I regress $\widehat{\omega_{nt}}(\beta_L, \beta_K)$ on a higher order polynomial of $\widehat{\omega_{n,t-1}}(\beta_L, \beta_K)$ along with the exit and export dummy. The residuals of this regression, denoted by $\widehat{\xi}_{nt}$, called the innovation to productivity, are then used to for the GMM estimation, by imposing the moment conditions given by

$$E\left[\widehat{\xi}_{nt}(\beta_L, \beta_K)\begin{pmatrix} k_{nt} \\ l_{n,t-1} \\ l_{n,t-1}^2 \end{pmatrix}\right] = 0.$$

For the GMM regression I use the R-package **gmm** (Chaussé, 2010). The the R command **gmm()** requires first to define a function that returns a matrix where each column contains a moment conditions. I call this function "Moment_f". In the formals of the function I define "theta", the set of parameters to be estimated, and "data", a data.table object containing all necessary variables. The following chunk code illustrates the implementation of the estimation routine.

```
library(np)
library(gmm)
library(data.table)

# Moments function
Moment_f <- function(theta, data){

  # Specify the production function parameters
  betaL = theta[1]; betaK = theta[2]

  # Data
  # First step nonparametric estimate and its lagged values
  phi_hat <- data[,"phi_hat"] ;  phi_hat_l1 <- data[,"phi_hat_l1"]

  # Explanatory variables its lagged values
```

```
  # Capital
  k <- data[, "k"] ; k_l1 <- data[, "k_l1"]
  # Labor
  l <- data[, "l"] ; l_l1 <- data[, "l_l1"]
  # Exit/export dummy
  X <- data,[,"X"] ; EXP <- data[,"EXP"]

  # Instruments
  z1 <- k; z2 <- l_l1; z3 <- l_l1^2

  # Moment matrix (to be returned by the function)
  Mom <- matrix(NA, nrow = nrow(data), ncol = 3)

  # Generate omega (firm productivity) and its lagged values
  omega  <- phi_hat -  betaL*l- betaK*k
  omega_lag <- phi_hat_l1 - betaL*l_l1- betaK*k_l1
  omega_lag_pol <- cbind(1, omega_lag, omega_lag^2, omega_lag^3)

  # Regress omega on its lagged values (using a 3rd order polynomial)
  # and in exit/export dummy and recover residuals

  # Right-hand-side variables
  reg_vars = cbind(omega_lag_pol, X, EXP)

  # Residuals (innovation to productivity)
  resid <- resid(lm(omega ~ reg_vars - 1))

  # Specify moments
  # (supposed to be in expectation orthogonal to the innovations)
  Mom[,1] <- z1*resid; Mom[,2] <- z2*resid; Mom[,3] <- z3*resid

  return(Mom)
}

# First stage non-parametric estimation
# Note: The dummy variables X and EXP identify firms activity and export statu
#       X = 1, if firms is about to exit and 0 else
#       EXP = 1, if firm exports and 0 else
data$phi_hat = fitted(npreg(q ~ l + k + m + factor(X) + factor(EXP),
```

```
                                          bwmethod = "cv.aic", data = data))

# Creation of lagged variables
data[, phi_hat_l1 := lag(phi_hat,1), by = "id" ]
data[, l_l1 := shift(l,1), by = "id" ]
data[, k_l1 := shift(k,1), by = "id" ]

# Second stage GMM estimation
# Note: a) Take OLS estimates as initial values
#       b) Use "optimal" weighting matrix
#       c) use "optim" as numeric optimizer (default Nelder-Mead algo.)
t0 = coefficients(lm(y ~ l + k, data = data))[2:3]

res.gmm <- gmm(g = Moment_f, x = as.matrix(na.omit(data))),
                t0 = t0, wmatrix = "optimal", optfct = "optim")
```

2.11.2 Production function estimates

Table 2.16 presents the production function estimates according to Ackerberg et al. (2015). The estimation routine is based on non-linear optimisation within the parameter space of the production function parameters β_L and β_K, by imposing the moment conditions, given in equation (2.5). The initial values for the non-linear optimization are chosen by the corresponding parameter estimates from the OLS regression, given in Table 2.17 below. For each 4-digit sector, the parameters are estimated for the sub-periods, 1994-2007 and 2008-2016. The J-Test or test for overidentification, given in the bottom of each output table, does not reject the H_0, indicating for all sectors and periods valid instruments, implying consistent estimation of the parameters. Note that based on these estimates, the Wald-test for structural stability between both periods is applied.

Table 2.16: Production function estimates (ACF)[a,b,c]

	Sawmilling/ wood planning 1610		Veneer sheets/wood-based panels/parquet floors 1621/22		Other builders' carpentry/joinery 1623	
	1994-2007	2008-2016	1994-2007	2008-2016	1994-2007	2008-2016
$\widehat{\beta}_L$	0.836***	1.019***	0.747***	0.641***	0.858***	0.662***
	(0.008)	(0.011)	(0.077)	(0.240)	(0.020)	(0.139)
$\widehat{\beta}_K$	0.181***	0.080***	0.327***	0.191	0.162***	0.495**
	(0.004)	(0.005)	(0.044)	(0.165)	(0.011)	(0.238)
OID-Test	0.962	0.764	0.863	0.620	0.855	0.868
# Firms	1720	1111	165	132	1094	938
# Obs.	12,192	5,445	1,296	590	7,033	4,299
	Wooden containers 1624		Other wood products 1629		Pulp, paper, paperboard 1711/12	
	1994-2007	2008-2016	1994-2007	2008-2016	1994-2007	2008-2016
$\widehat{\beta}_L$	0.937***	0.890***	0.907***	0.988***	0.976***	1.183***
	(0.008)	(0.014)	(0.035)	(0.037)	(0.146)	(0.115)
$\widehat{\beta}_K$	0.101***	0.125***	0.185***	0.138***	0.177**	0.036***
	(0.005)	(0.008)	(0.011)	(0.016)	(0.075)	(0.014)
OID-Test	0.835	0.999	0.945	0.918	0.898	0.913
# Firms	891	626	503	249	198	131
# Obs.	6,317	3,404	3,367	1,159	1,532	678
	Cardboard/packaging domestic/health usage 1721/22		Other products of paper 1723/24/29		Office/shop furniture 3101	
	1994-2007	2008-2016	1994-2007	2008-2016	1994-2007	2008-2016
$\widehat{\beta}_L$	0.884***	0.903***	0.852***	0.816***	0.788***	1.029***
	(0.018)	(0.012)	(0.025)	(0.021)	(0.012)	(0.013)
$\widehat{\beta}_K$	0.167***	0.130***	0.139***	0.104***	0.150***	0.012
	(0.009)	(0.008)	(0.015)	(0.014)	(0.007)	(0.010)
OID-Test	0.784	0.671	0.838	0.937	0.95	0.953
# Firms	811	579	528	395	745	617
# Obs	6,293	3,166	3,948	2,072	4,986	3,106
	Office/shop furniture 3102		Kitchen furniture 3109			
	1994-2007	2008-2016	1994-2007	2008-2016		
$\widehat{\beta}_L$	0.970***	1.016***	0.789***	0.845***		
	(0.033)	(0.132)	(0.009)	(0.027)		
$\widehat{\beta}_K$	0.062***	0.018	0.208***	0.091***		
	(0.018)	(0.030)	(0.005)	(0.010)		
OID-Test	0.757	0.823	0.298	0.802		
# Firms	407	282	2095	738		
# Obs	2,733	1,232	12,304	2,984		

[a] Standard errors are bootstrapped using 400 replications and given in parenthesis.

[b] *p<0.1; **p<0.05; ***p<0.01.

[c] The OID-Test reports p-values of the overidentification test for validity of the instruments. A p-value > 0.05 indicates validity of the instruments.

Table 2.17: Production function OLS estimates[a,b]

	Sawmilling/ wood planning 1610		Veneer sheets/wood-based panels/parquet floors 1621/22		Other builders' carpentry/joinery 1623	
	1994-2007	2008-2016	1994-2007	2008-2016	1994-2007	2008-2016
$\widehat{\beta}_L$	0.867***	0.987***	0.774***	0.862***	0.849***	0.929***
	(0.008)	(0.013)	(0.029)	(0.051)	(0.011)	(0.013)
$\widehat{\beta}_K$	0.170***	0.077***	0.277***	0.212***	0.194***	0.093***
	(0.004)	(0.006)	(0.018)	(0.031)	(0.007)	(0.008)
Constant	−0.490***	−0.289***	−0.471***	−0.510***	−0.458***	−0.276***
	(0.018)	(0.027)	(0.064)	(0.112)	(0.025)	(0.027)
# Obs	12,192	5,445	1,296	590	7,033	4,299
R^2	0.726	0.686	0.854	0.762	0.789	0.790
	Wooden containers 1624		Other wood products 1629		Pulp, paper, paperboard 1711/12	
	1994-2007	2008-2016	1994-2007	2008-2016	1994-2007	2008-2016
$\widehat{\beta}_L$	0.908***	0.896***	0.843***	0.908***	0.788***	1.039***
	(0.012)	(0.015)	(0.017)	(0.028)	(0.023)	(0.036)
$\widehat{\beta}_K$	0.139***	0.119***	0.171***	0.117***	0.284***	0.122***
	(0.008)	(0.009)	(0.011)	(0.017)	(0.014)	(0.021)
Constant	−0.571***	−0.191***	−0.572***	−0.349***	−0.400***	−0.439***
	(0.028)	(0.033)	(0.039)	(0.061)	(0.054)	(0.085)
# Obs	6,317	3,404	3,367	1,159	1,532	678
R^2	0.737	0.734	0.703	0.662	0.908	0.883
	Cardboard/packaging domestic/health usage 1721/22		Other products of paper 1723/24/29		Office/shop furniture 3101	
	1994-2007	2008-2016	1994-2007	2008-2016	1994-2007	2008-2016
$\widehat{\beta}_L$	0.884***	0.837***	0.805***	0.779***	0.866***	0.974***
	(0.011)	(0.015)	(0.016)	(0.021)	(0.012)	(0.014)
$\widehat{\beta}_K$	0.164***	0.171***	0.168***	0.123***	0.141***	0.050***
	(0.007)	(0.010)	(0.011)	(0.014)	(0.008)	(0.009)
Constant	−0.486***	−0.092***	−0.154***	0.222***	−0.205***	−0.179***
	(0.025)	(0.033)	(0.035)	(0.045)	(0.029)	(0.029)
# Obs	6,293	3,166	3,948	2,072	4,986	3,106
R^2	0.866	0.840	0.777	0.714	0.808	0.824
	Office/shop furniture 3102		Kitchen furniture 3109			
	1994-2007	2008-2016	1994-2007	2008-2016		
$\widehat{\beta}_L$	0.961***	0.989***	0.958***	0.938***		
	(0.017)	(0.027)	(0.009)	(0.017)		
$\widehat{\beta}_K$	0.136***	0.068***	0.132***	0.063***		
	(0.012)	(0.019)	(0.006)	(0.011)		
Constant	−0.839***	−0.673***	−0.812***	−0.397***		
	(0.037)	(0.051)	(0.020)	(0.037)		
# Obs	2,733	1,232	12,304	2,984		
R^2	0.857	0.821	0.780	0.742		

[a] Standard errors are given in parenthesis.
[b] *p<0.1; **p<0.05; ***p<0.01.

2.11.3 Distribution of the production function residual

The production function estimation presumes zero mean of the error term ϵ_{nt} (see the regression equation (2.1)). After the nonparametric first step regression the corresponding residuals, $\widehat{\epsilon}_{nt}$, can be obtained according to equation (2.3). The residuals are then in further use when estimating firm-level productivity, $\widehat{\omega}_{nt}$, shown in equation (2.6). To provide some information on $\widehat{\epsilon}_{nt}$, Figure 2.10 shows the distribution for both sub-periods, with a strong symmetric concentration around zero.

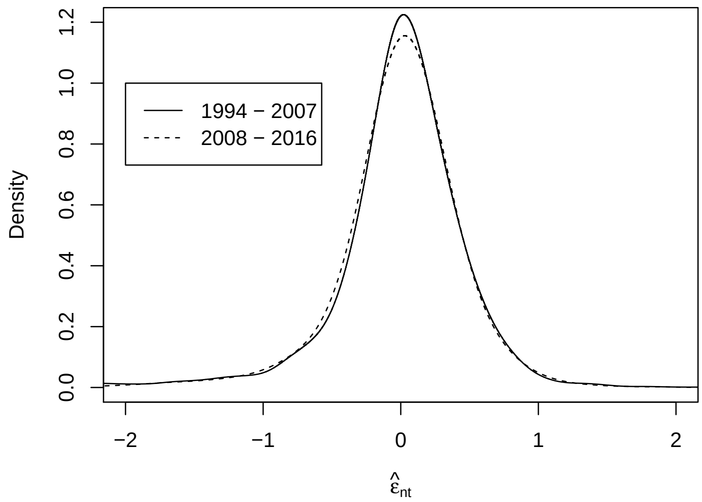

Figure 2.10: Distribution of the production function residual

2.12 Appendix D: Productivity distribution and dispersion by 4-digit sector

This sections provides some further results concerning changes in the productivity dispersion by sector. Table 2.18 illustrates the percentile ratios of the productivity distribution w.r.t. the period 1994-2007 and 2007-2016, given in Panel A and B, respectively (over all firms and w.r.t. each sector separately). The table shows that the productivity dispersion has increased within almost all sectors, as the percentile rations increase between the two periods. For the sectors 1621/22 and 1623 I measure a massive increase especially in the 99/1 percentile ratio, indicating that in these sectors the most productive firms (at the 99*th* percentile of the productivity distribution) have substantially more increased their productivity compared to the less productive firms (at the 1*th* percentile of the productivity distribution).

Table 2.18: Percentile-ratios of the productivity distribution by 4-digit sector

Panel A: 1994-2007

	Sector*											
	All	1610	1621/22	1623	1624	1629	1711/12	1721/22	1723/24/29	3101	3102	3109
90/10	2.04	1.62	2.23	1.77	1.47	1.69	2.44	1.47	1.66	1.85	1.93	1.72
95/5	2.71	2.00	3.82	2.17	1.81	2.14	3.33	1.79	2.22	2.30	2.39	2.06
99/1	5.46	4.23	25.18	4.00	3.66	5.38	11.07	3.53	6.94	4.35	5.07	3.34

Panel B: 2008-2016

	Sector*											
	All	1610	1621/22	1623	1624	1629	1711/12	1721/22	1723/24/29	3101	3102	3109
90/10	2.45	1.71	3.12	3.11	1.77	2.06	2.84	1.79	1.88	1.64	1.60	1.70
95/5	3.38	2.13	5.24	4.76	2.34	2.79	4.41	2.40	2.85	2.03	1.96	2.13
99/1	9.40	5.33	44.40	18.36	4.16	6.21	31.30	5.49	9.75	4.27	3.52	5.07

* 1610 - sawmilling/wood planning, 1621/22 - veneer sheets/wood-based panels/parquet floors, 1623 - other builders' carpentry/joinery, 1624 - wooden containers, (1629) other products of wood, 1711/12 - pulp, paper, and paperboard, 1721/22 - cardboard/packaging/paper for domestic and health usage, 1723/24/29 - other products of paper, 3101 - office/shop furniture, 3102 kitchen furniture, (3109) other furniture.

2.13 Appendix E: Productivity decomposition

This section provides more empirical results w.r.t. the various applied aggregate productivity decompositions in this chapter. Section 2.13.1 provides further material concerning the yearly aggregate productivity decomposition with entry and exit. Section 2.13.2 applies the DOPD approach for each 4-digit industry separately. Section 2.13.3 provides further empirical results concerning the productivity decomposition w.r.t. firms export status and Section 2.13.3 does the same concerning the productivity decomposition w.r.t. firms' domestic and export sales activity.

2.13.1 Annual aggregate productivity with entry and exit

Table 2.19 provides figures w.r.t. aggregate productivity and sales shares of the firm groups survivors, entrants, and exitors. Note that Figure 2.4 in the main text can directly be reproduced using the aggregate productivity measures for the three firm groups ($\Omega_{S,t}, \Omega_{E,t}, \Omega_{X,t}$). Figure 2.5, showing the contribution to aggregate productivity growth by the three firm groups, can be deduced from Table 2.19, by applying the DOPD decomposition, given in equation (2.11).

Table 2.19: Aggregate productivity and sales shares over all firms*

Year	$S_{S,t}$	# Surv.	$S_{E,t}$	# Entr.	$S_{X,t}$	# Exit.	Ω_t	$\Omega_{S,t}$	$\Omega_{E,t}$	$\Omega_{X,t}$
1995	92.66	4539	5.04	466	2.26	135	-0.503	-0.494	-0.756	-0.298
1996	95.16	4780	2.08	325	2.36	312	-0.513	-0.508	-0.576	-0.528
1997	93.98	4895	2.70	366	3.13	266	-0.475	-0.468	-0.632	-0.491
1998	95.53	5133	1.71	205	2.62	254	-0.459	-0.462	-0.206	-0.528
1999	94.62	5088	2.60	191	2.51	344	-0.440	-0.445	-0.546	-0.196
2000	96.33	4879	1.65	175	1.59	317	-0.434	-0.428	-0.611	-0.575
2001	96.06	4997	2.01	359	1.90	145	-0.413	-0.415	-0.376	-0.386
2002	93.98	4976	1.54	248	4.29	312	-0.414	-0.413	-0.245	-0.501
2003	94.25	5015	2.68	241	3.03	239	-0.381	-0.389	-0.376	-0.116
2004	93.74	4940	1.99	157	3.69	249	-0.400	-0.405	-0.384	-0.294
2005	94.94	4865	3.15	141	1.83	128	-0.374	-0.369	-0.428	-0.552
2006	94.62	4831	1.17	197	4.07	204	-0.341	-0.341	-0.232	-0.358
2007	94.37	4824	3.58	163	1.95	210	-0.348	-0.357	-0.362	0.135
2008	95.16	4358	0.88	94	3.77	252	-0.175	-0.171	-0.199	-0.289
2009	93.91	4127	3.16	89	2.73	184	-0.219	-0.223	-0.207	-0.103
2010	93.69	4024	2.95	105	2.89	155	-0.226	-0.243	0.216	-0.200
2011	94.65	3888	1.91	110	3.23	222	-0.258	-0.262	-0.072	-0.281
2012	95.90	3800	2.18	131	1.68	117	-0.239	-0.244	-0.160	-0.099
2013	98.06	3747	0.77	79	1.07	95	-0.219	-0.217	-0.157	-0.441
2014	95.41	3603	2.07	84	2.26	91	-0.198	-0.205	0.439	-0.540
2015	95.51	3474	3.29	81	1.14	92	-0.169	-0.196	0.567	-0.089

* The columns $S_{G,t}$ and $\Omega_{G,t}$ with $G = \{S, E, X\}$ denote the aggregate sales share and the aggregate productivity of the firm groups survivors, exitors, and entrants, measured at the respective year. All sales shares $S_{G,t}$ are given in %.

2.13.2 Aggregate productivity and entry and exit w.r.t. 4-digit sectors

This section present the results of the DOPD for each 4-digit sector separately, given in Table 2.20. Further bellow, Table 2.21 and 2.22 provide measures of aggregate productivity and sales shares of the firm groups survivors, exitors, and entrants (likewise for each 4-digit sector separately), from which the growth rates reported in Table 2.20 can be derived. Note that Table 2.21 illustrates the empirical results associated with equation (2.9), the measures related to the initial year of a given period, i.e. measuring at Year 1 the aggregates for those firms that survive and exit until Year 2. Instead, Table 2.22 is associated with equation (2.10), i.e. measuring at Year 2 the aggregates for those firms that survive and enter until Year 2.

Generally, Table 2.20 shows that the evolution of aggregate productivity growth varies substantially among the different 4-digit sectors. However, there are some patters in common. First, many sectors reveal a considerable productivity growth for the initial period, 1994-2000, whereupon a decline in the growth rate is observed. Second, for most sectors the period of crisis 2008-2012, is marked with relatively low or negative growth in aggregate productivity. Third, for most cases, the group of surviving firms contributes most to aggregate productivity growth. Fourth, firms' entry and exit contribution is less important for the overall aggregate productivity growth.

The table, however, also provides interesting information regarding to some specific sectors: For instance, considering the sector for wood-based panels/parquet floors (1621/22), the within contribution, i.e. firms average productivity improvement through learning is negative throughout the whole periods. Instead, the positive between contribution, i.e. reallocation effects of sales shares moving from less to more productive firms, fully compensates the negative within contribution. Furthermore, for most years and periods, the three manufacturing sectors for products of furniture (3101, 3102, and 3103) experience negative between-contribution of surviving firms, indicating inefficient allocation of sales shares. Also, for some sectors, the contribution of entering and exiting firms is substantial: For example, the industry for wood-based panels reveals a quite consistent negative (positive) contribution of the group of entrants (exitors). According to the DOPD approach, this implies that entrants and exitors are relatively less productive compared to the group of surviving firms. A similar pattern can be seen for the sector 1721/21.

Table 2.20: Aggregate productivity growth (DOPD) w.r.t. 4-digit sectors[a]

Sector	Period	Total Growth[b]	Contribution Survivors Within	Contribution Survivors Between	Contribution Entrants	Contribution Exitors
11610	1994 - 2000	3.25 (0.53)	7.33 (1.19)	-5.98 (-0.97)	0.87 (0.14)	1.03 (0.17)
Sawmilling/	2001 - 2007	18.89 (2.93)	9.73 (1.56)	7.14 (1.16)	-0.61 (-0.10)	2.63 (0.43)
wood planning	2008 - 2012	-8.48 (-2.06)	1.46 (0.36)	-6.73 (-1.64)	-1.09 (-0.27)	-2.11 (-0.52)
	2013 - 2016	16.89 (5.34)	4.90 (1.61)	7.99 (2.60)	0.23 (0.08)	3.77 (1.24)
1621/22	1994 - 2000	4.65 (0.76)	-6.31 (-1.03)	4.82 (0.79)	3.21 (0.53)	2.93 (0.48)
wood-based	2001 - 2007	7.23 (1.17)	-6.50 (-1.06)	12.13 (1.93)	-0.18 (-0.03)	1.77 (0.29)
panels/parquet floors	2008 - 2012	1.62 (0.40)	-7.65 (-1.86)	7.99 (1.94)	-3.50 (-0.86)	4.79 (1.18)
	2013 - 2016	3.09 (1.02)	-4.31 (-1.42)	7.77 (2.53)	-1.67 (-0.56)	1.30 (0.43)
1623	1994 - 2000	4.88 (0.80)	8.06 (1.30)	-4.73 (-0.77)	1.50 (0.25)	0.05 (0.01)
Other builders'	2001 - 2007	6.14 (1.00)	10.78 (1.72)	0.28 (0.05)	-2.13 (-0.35)	-2.78 (-0.46)
carpentry/joinery	2008 - 2012	-15.76 (-3.73)	-14.63 (-3.47)	-2.86 (-0.71)	2.72 (0.67)	-0.99 (-0.25)
	2013 - 2016	-4.58 (-1.50)	-22.97 (-7.13)	14.68 (4.67)	5.69 (1.86)	-1.98 (-0.66)
1624	1994 - 2000	20.45 (3.15)	8.56 (1.38)	14.21 (2.24)	-2.46 (-0.41)	0.14 (0.02)
Wooden containers	2001 - 2007	7.03 (1.14)	6.99 (1.13)	0.71 (0.12)	-0.43 (-0.07)	-0.24 (-0.04)
	2008 - 2012	-6.81 (-1.66)	-3.65 (-0.90)	-2.58 (-0.64)	-1.93 (-0.48)	1.35 (0.34)
	2013 - 2016	-2.70 (-0.89)	-1.77 (-0.59)	-0.97 (-0.32)	-0.16 (-0.05)	0.20 (0.07)
1629	1994 - 2000	13.03 (2.06)	0.31 (0.05)	15.18 (2.38)	-2.24 (-0.37)	-0.21 (-0.04)
Other wood	2001 - 2007	-11.47 (-1.83)	1.96 (0.32)	3.36 (0.55)	-0.46 (-0.08)	-16.34 (-2.55)
products	2008 - 2012	19.92 (4.65)	2.01 (0.50)	11.52 (2.76)	-0.65 (-0.16)	7.03 (1.71)
	2013 - 2016	14.97 (4.76)	-0.07 (-0.02)	0.88 (0.29)	14.20 (4.52)	-0.03 (-0.01)
1711/12	1994 - 2000	7.11 (1.15)	5.01 (0.82)	4.35 (0.71)	-1.37 (-0.23)	-0.88 (-0.15)
Pulp and	2001 - 2007	13.68 (2.16)	8.93 (1.44)	2.17 (0.36)	2.74 (0.45)	-0.16 (-0.03)
paper	2008 - 2012	6.65 (1.62)	2.26 (0.56)	3.07 (0.76)	-0.95 (-0.24)	2.27 (0.56)
	2013 - 2016	8.72 (2.83)	2.20 (0.73)	7.11 (2.32)	-0.82 (-0.27)	0.23 (0.08)
1721/22	1994 - 2000	10.41 (1.66)	3.12 (0.51)	6.74 (1.09)	-0.37 (-0.06)	0.93 (0.15)
Cardboard/packaging/	2001 - 2007	4.63 (0.76)	2.28 (0.38)	1.20 (0.20)	-0.30 (-0.05)	1.45 (0.24)
domestic/health usage	2008 - 2012	-0.01 (0.00)	1.15 (0.29)	-3.39 (-0.84)	1.20 (0.30)	1.03 (0.26)
	2013 - 2016	-2.16 (-0.71)	-0.68 (-0.22)	-1.96 (-0.65)	-0.02 (-0.01)	0.50 (0.17)
1723/24/29	1994 - 2000	-5.13 (-0.84)	1.13 (0.19)	-7.67 (-1.24)	5.99 (0.97)	-4.58 (-0.75)
Other products	2001 - 2007	1.68 (0.28)	1.18 (0.20)	7.77 (1.25)	-0.96 (-0.16)	-6.31 (-1.02)
of paper	2008 - 2012	6.42 (1.57)	3.46 (0.85)	6.47 (1.58)	2.46 (0.61)	-5.96 (-1.46)
	2013 - 2016	-5.53 (-1.81)	-3.94 (-1.30)	-1.65 (-0.55)	0.61 (0.20)	-0.55 (-0.18)
3101	1994 - 2000	33.39 (4.92)	26.64 (4.01)	13.78 (2.17)	-3.87 (-0.64)	-3.15 (-0.52)
Office/shop	2001 - 2007	6.08 (0.99)	11.51 (1.83)	-7.20 (-1.17)	-1.53 (-0.25)	3.30 (0.54)
furniture	2008 - 2012	-6.68 (-1.63)	-3.12 (-0.77)	-10.47 (-2.52)	6.05 (1.48)	0.86 (0.21)
	2013 - 2016	8.77 (2.84)	1.11 (0.37)	7.00 (2.28)	0.29 (0.10)	0.37 (0.12)
3102	1994 - 2000	-3.55 (-0.58)	13.17 (2.08)	-17.29 (-2.69)	0.44 (0.07)	0.12 (0.02)
Kitchen	2001 - 2007	-4.82 (-0.79)	9.77 (1.57)	-13.22 (-2.09)	-0.86 (-0.14)	-0.51 (-0.08)
furniture	2008 - 2012	-5.89 (-1.44)	-1.41 (-0.35)	-1.68 (-0.42)	0.83 (0.21)	-3.63 (-0.90)
	2013 - 2016	20.15 (6.31)	4.52 (1.48)	16.57 (5.24)	-0.77 (-0.26)	-0.17 (-0.06)
3109	1994 - 2000	-0.40 (-0.07)	10.12 (1.62)	-11.45 (-1.82)	1.54 (0.25)	-0.60 (-0.10)
Other	2001 - 2007	3.08 (0.51)	-0.23 (-0.04)	-1.51 (-0.25)	1.27 (0.21)	3.55 (0.58)
furniture	2008 - 2012	-6.77 (-1.65)	-3.62 (-0.89)	-5.20 (-1.27)	-0.72 (-0.18)	2.76 (0.68)
	2013 - 2016	-12.64 (-4.05)	-1.45 (-0.48)	-10.31 (-3.32)	-1.22 (-0.41)	0.35 (0.12)

[a] All figures represent growth rates in % relative to the initial year of the given period. Average annual growth rates are given in parenthesis.

[b] The total growth in aggregate productivity is the sum of the contributions of survivors, entrants and exitors.

Table 2.21: Aggregate productivity and sales shares by 4-digit sectors (Year 1)*

			Measures at Year 1					
Sector	Year 1	Year 2	$\Omega_{S,1}$	$S_{S,1}$	$\Omega_{X,1}$	$S_{X,1}$	No. Surv.	No. Exitors
1610	1994	2000	-0.53	87.85	-0.61	12.15	664	102
Sawmilling/	2001	2007	-0.42	77.93	-0.54	22.07	710	176
wood planning	2008	2012	-0.26	86.94	-0.10	13.06	541	100
	2013	2016	-0.31	95.98	-1.25	4.02	555	38
1621/22	1994	2000	-0.52	87.57	-0.75	12.43	70	9
Wood-based	2001	2007	-0.48	86.81	-0.62	13.19	81	15
panels/parquet floors	2008	2012	1.07	80.54	0.83	19.46	60	16
	2013	2016	1.04	98.53	0.15	1.47	55	3
1623	1994	2000	-0.45	86.11	-0.46	13.89	318	84
Other builders'	2001	2007	-0.40	74.68	-0.29	25.32	452	96
carpentry/joinery	2008	2012	-0.49	87.07	-0.42	12.93	422	109
	2013	2016	-0.67	94.08	-0.34	5.92	413	50
1624	1994	2000	-0.64	85.72	-0.65	14.28	350	75
Wooden containers	2001	2007	-0.43	84.83	-0.42	15.17	363	94
	2008	2012	-0.01	89.41	-0.14	10.59	348	46
	2013	2016	-0.05	97.50	-0.13	2.50	375	21
1629	1994	2000	-0.81	86.41	-0.79	13.59	195	33
Other wood	2001	2007	-0.72	69.44	-0.18	30.56	170	53
products	2008	2012	-0.56	72.87	-0.82	27.13	125	43
	2013	2016	-0.45	90.27	-0.45	9.73	104	12
1711/12	1994	2000	-0.89	84.63	-0.84	15.37	81	18
Pulp and	2001	2007	-0.78	83.85	-0.77	16.15	91	21
paper	2008	2012	-0.68	91.62	-0.95	8.38	71	15
	2013	2016	-0.69	88.91	-0.71	11.09	70	8
1721/22	1994	2000	-0.46	90.11	-0.55	9.89	382	73
cardboard/packaging/	2001	2007	-0.37	74.28	-0.43	25.72	354	119
domestic/health usage	2008	2012	-0.13	88.70	-0.22	11.30	329	55
	2013	2016	-0.09	96.68	-0.24	3.32	378	22
1723/24/29	1994	2000	-0.21	80.16	0.02	19.84	226	43
Other products	2001	2007	-0.13	82.51	0.23	17.49	229	52
of paper	2008	2012	0.14	80.88	0.45	19.12	205	26
	2013	2016	0.30	93.28	0.38	6.72	243	11
3101	1994	2000	-0.08	72.59	0.04	27.41	229	55
Office/shop	2001	2007	0.34	80.83	0.17	19.17	320	79
furniture	2008	2012	-0.15	86.77	-0.22	13.23	323	61
	2013	2016	-0.16	92.66	-0.21	7.34	308	35
3102	1994	2000	-0.59	90.81	-0.60	9.19	120	32
Kitchen	2001	2007	-0.59	92.05	-0.53	7.95	159	27
furniture	2008	2012	-0.57	86.71	-0.29	13.29	123	30
	2013	2016	-0.54	96.38	-0.50	3.62	102	13
3109	1994	2000	-0.38	83.59	-0.34	16.41	630	202
Other	2001	2007	-0.37	80.56	-0.56	19.44	597	246
furniture	2008	2012	0.15	84.05	-0.02	15.95	318	141
	2013	2016	0.23	93.72	0.17	6.28	225	34

* The columns $\Omega_{G,1}$ and $S_{G,1}$ with $G = \{S, X\}$ denote the aggregate productivity and the aggregate sales share of the firm groups survivors, exitors, and entrants - measured for the initial year (Year 1) of the period. All sales shares $S_{G,1}$ are given in %.

Table 2.22: Aggregate productivity and sales shares by sector (Year 2)*

			Measures at Year 2					
Sector	Year 1	Year 2	$\Omega_{S,2}$	$S_{S,2}$	$\Omega_{E,2}$	$S_{E,2}$	No. Surv.	No. Entrants
1610	1994	2000	-0.52	85.99	-0.45	14.01	664	192
Sawmilling/	2001	2007	-0.25	86.15	-0.30	13.85	710	172
wood planning	2008	2012	-0.32	91.60	-0.45	8.40	541	62
	2013	2016	-0.18	97.22	-0.10	2.78	555	21
1621_22	1994	2000	-0.53	82.45	-0.35	17.55	70	16
Wood-based	2001	2007	-0.43	77.86	-0.44	22.14	81	15
panels	2008	2012	1.08	97.82	-0.53	2.18	60	4
	2013	2016	1.07	93.96	0.79	6.04	55	4
1623	1994	2000	-0.42	86.94	-0.30	13.06	318	163
Other builders'	2001	2007	-0.28	81.78	-0.40	18.22	452	151
carpentry/joinery	2008	2012	-0.67	86.33	-0.47	13.67	422	59
	2013	2016	-0.76	94.99	0.38	5.01	413	24
1624	1994	2000	-0.42	82.27	-0.55	17.73	350	111
Wooden containers	2001	2007	-0.36	91.60	-0.41	8.40	363	63
	2008	2012	-0.07	86.14	-0.21	13.86	348	47
	2013	2016	-0.08	99.10	-0.26	0.90	375	11
1629	1994	2000	-0.65	84.62	-0.80	15.38	195	49
Other wood	2001	2007	-0.67	88.45	-0.71	11.55	170	31
products	2008	2012	-0.42	95.17	-0.56	4.83	125	7
	2013	2016	-0.45	74.06	0.10	25.94	104	4
1711/12	1994	2000	-0.80	69.98	-0.85	30.02	81	31
Pulp and	2001	2007	-0.67	91.46	-0.35	8.54	91	19
paper	2008	2012	-0.63	94.55	-0.80	5.45	71	8
	2013	2016	-0.60	85.75	-0.66	14.25	70	8
1721/22	1994	2000	-0.36	93.00	-0.41	7.00	382	88
cardboard/packaging/	2001	2007	-0.34	84.28	-0.36	15.72	354	58
domestic/health usage	2008	2012	-0.15	91.66	-0.01	8.34	329	33
	2013	2016	-0.12	97.98	-0.13	2.02	378	8
1723/24/29	1994	2000	-0.28	83.38	0.08	16.62	226	47
Other products	2001	2007	-0.04	92.23	-0.16	7.77	229	39
of paper	2008	2012	0.24	80.12	0.37	19.88	205	25
	2013	2016	0.24	92.47	0.33	7.53	243	7
3101	1994	2000	0.33	81.93	0.11	18.07	229	120
Office/shop	2001	2007	0.39	87.20	0.27	12.80	320	86
furniture	2008	2012	-0.29	84.35	0.10	15.65	323	20
	2013	2016	-0.08	97.73	0.05	2.27	308	10
3102	1994	2000	-0.63	81.01	-0.61	18.99	120	63
Kitchen	2001	2007	-0.63	92.94	-0.75	7.06	159	43
furniture	2008	2012	-0.60	92.44	-0.49	7.56	123	12
	2013	2016	-0.33	94.10	-0.46	5.90	102	6
3109	1994	2000	-0.39	89.22	-0.25	10.78	630	216
Other	2001	2007	-0.39	90.90	-0.25	9.10	597	134
furniture	2008	2012	0.06	87.22	0.01	12.78	318	32
	2013	2016	0.11	95.94	-0.19	4.06	225	18

* The columns $\Omega_{G,2}$ and $S_{G,2}$ with $G = \{S, E\}$, denote the aggregate productivity and the aggregate sales share of the firm groups survivors, exitors, and entrants - measured for the last year of the period (Year 2). All sales shares $S_{G,2}$ are given in %.

2.13.3 Aggregate productivity and firms' export behavior

Aggregate productivity decomposition w.r.t. export status

Table 2.23 provides measures of aggregate productivity and sales shares of the firm groups survivors, exitors, and entrants, separately for the firm categories non-exporter and exporter. Note that Panel A illustrates the empirical results associated with equation (2.9), the measures related to the initial year of a given period, i.e. measuring at Year 1 aggregate productivity/sales shares for those firms that survive and exit until Year 2. Panel B is associated with equation (2.10), i.e. measuring at Year 2 the aggregate productivity/sales shares for those firms that survive and enter until Year 2. Note that, here sales shares of both the group of non-exporter and exporter sum up to 100% for a given year. For instance, consider Panel A, period 1994 (Year1) - 2000 (Year 2), the aggregate sales shares of group of surviving (exiting) firms belonging the group of non-exporter is given in 1994 by 11.21% (2.01%). For the same period, the sales shares of the surviving (exiting) firms belonging to the group of exporter is given in 1994 (Panel A) by 74.49% (12.29%), which in total yields 100%. Similarly, to obtain the total number of surviving firms, one needs to sum up surviving firms belonging to the group of non-exporter and exporter, given by 1484 and 1781, yielding a total of surviving firms of 3265. Note that this number of survivors was also reported in Table 2.8 when considering all firms irrespective of their export status.

Table 2.23: Aggregate productivity and sales shares: domestic and export firms[a]

			Panel A: Measures at Year 1					
	Year 1	Year 2	$\Omega_{S,1}$	$S_{S,1}$	$\Omega_{X,1}$	$S_{X,1}$	No. Surv.	No. Exitors
Non-exporter	1994	2000	-0.555	11.21	-0.502	2.01	1484	400
	2001	2007	-0.429	10.94	-0.339	2.85	1676	510
	2009	2012	-0.242	13.43	-0.282	2.06	1506	260
	2013	2016	-0.299	14.66	-0.296	0.88	1395	140
Exporter	1994	2000	-0.529	74.49	-0.478	12.29	1781	326
	2001	2007	-0.420	69.18	-0.418	17.03	1850	468
	2009	2012	-0.217	78.05	-0.159	6.45	1713	219
	2013	2016	-0.167	79.67	-0.438	4.79	1539	108
			Panel B: Measures at Year 2					
	Year 1	Year 2	$\Omega_{S,2}$	$S_{S,2}$	$\Omega_{E,2}$	$S_{E,2}$	No. Surv.	No. Entrants
Non-exporter	1994	2000	-0.461	9.90	-0.450	3.02	1375	627
	2001	2007	-0.315	11.11	-0.300	2.86	1639	545
	2009	2012	-0.328	13.88	-0.210	1.47	1557	154
	2013	2016	-0.289	14.38	-0.040	0.58	1343	62
Exporter	1994	2000	-0.428	73.80	-0.530	13.27	1890	469
	2001	2007	-0.362	76.36	-0.328	9.67	1887	266
	2009	2012	-0.205	78.40	-0.143	6.25	1662	135
	2013	2016	-0.138	79.64	-0.220	5.40	1591	66

[a] The columns $\Omega_{G,j}$ and $S_{G,j}$ with $G = \{S, X, E\}$ and $j = \{1, 2\}$, denote the aggregate productivity and the aggregate sales share of the firm groups survivors, exitors, and entrants - measured for the initial year (Year 1) and the last year of the period (Year 2). All sales shares $S_{G,j}$ are given in %.

Investigating productivity differences w.r.t. firms' export status

I am interested in investigating productivity differences between the two firm groups of exporter and non-exporter. For this purpose, I follow Fariñas and Ruano (2005) who analyzed productivity differences for different groups of firms active in the Spanish manufacturing industry. The analysis is conducted in two parts: (i) by a graphically comparison between the empirical cumulative density function (ECDF) of the firms belonging to the different groups and (ii) by statistically testing differences among these distributions.

(i) Graphical comparison. In order to graphically analyze the distributions between different groups of firms I visualize the CDF's of the corresponding firm group. This allows to compare the whole productivity distributions of different groups of firms, instead of only comparing single moments, such as the mean or the median.

Let $\widehat{F}_G(c)$ be the productivity ECDF of a specific firm group, where

$$\widehat{F}_G(c) = \frac{1}{N_G} \sum_{n \in G} \mathbf{1}_{[\widehat{\omega}_n \leq c]}, \tag{2.16}$$

where $\mathbf{1}_{[A]}$ denotes a dummy variable equal to 1 if the condition A in brackets is satisfied and 0 otherwise. The intuition of the concept of (first-order) stochastic dominance is, if the position of productivity ECDF of group one is consistently located to the right of the ECDF of group two, then the distribution of group two stochastically dominates the distribution of group one. This implies that for each percentile, firms' productivity levels belonging to group two are higher compared to group one.

(ii) Testing procedure. Let F_1 and F_2 be the CDF's of firm productivity of exporters and non-exporters, respectively, for a given period t. First order stochastic dominance of F_1 with respect to F_2 implies $F_1(\omega) - F_2(\omega) \leq 0$, with strict inequality for a specific productivity level ω, where $P(\omega \in \mathbb{R}) = 1$. The Kolmogorov-Smirnov test allows to test for stochastic dominance.[35] First, the two-sided test allows to test whether the distributions F_1 and F_2 follow the same law and is given by

$$H_0 : \sup_{\omega \in \mathbb{R}} |F_1(\omega) - F_2(\omega)| = 0 \quad \text{vs.} \quad H_A : \sup_{\omega \in \mathbb{R}} |F_1(\omega) - F_2(\omega)| \neq 0, \tag{2.17}$$

The one-sided test, allows to specifically test which of the two distributions (first order) stochastically dominates the other and is given by

$$H_0 : \sup_{\omega \in \mathbb{R}} \{F_1(\omega) - F_2(\omega)\} \leq 0 \quad \text{vs.} \quad H_A : \sup_{\omega \in \mathbb{R}} \{F_1(\omega) - F_2(\omega)\} > 0. \tag{2.18}$$

[35] See Kolmogorov (1933) and Smirnov (1939).

The respective test statistics for the two- and one-side test are given by

$$\mathrm{KS}_N^{\mathrm{two}} = \sqrt{\frac{N_1 \cdot N_2}{N}} \sup_{\omega \in \mathbb{R}} |T_N(\omega)| \quad \text{and} \quad \mathrm{KS}_N^{\mathrm{one}} = \sqrt{\frac{N_1 \cdot N_2}{N}} \sup_{\omega \in \mathbb{R}} T_N(\omega), \tag{2.19}$$

where $T_N(\omega) = \widehat{F}_{1,N_1}(\omega) - \widehat{F}_{2,N_2}(\omega)$, with $\widehat{F}_{1,N_1}$ and $\widehat{F}_{2,N_2}$ the empirical CDF's of F_1 and F_2 and $N = N_1 + N_2$ denotes the total number of observations from both distributions.

Aggregate productivity w.r.t. firms' domestic and export activity

Table 2.24 relates to the productivity decomposition presented in equation (2.13), i.e. the Olley-Pakes productivity decomposition, extended to the case of domestic and export economic activity. The table shows both aggregate productivity and sales shares related to firms' domestic and export economic activity, measured at the initial year of a given period (Panel A) as well as at the end year of a given period (Panel B)

Table 2.24: Aggregate productivity and sales share w.r.t. firms domestic and export activity*

Year 1	Year 2	Ω_1	$S_{d,1}$	$\Omega_{d,1}$	$S_{exp,1}$	$\Omega_{exp,2}$	No. firms
Panel A: Measures at Year 1							
1994	2000	-0.542	76.87	-0.388	23.13	-0.154	3265
2001	2007	-0.441	72.70	-0.297	27.30	-0.144	3526
2009	2012	-0.229	76.47	-0.171	23.53	-0.059	3219
2013	2016	-0.202	77.34	-0.157	22.66	-0.046	2934
Panel B: Measures at Year 2							
Year 1	Year 2	Ω_2	$S_{d,2}$	$\Omega_{d,2}$	$S_{exp,2}$	$\Omega_{exp,2}$	No. firms
1994	2000	-0.448	75.40	-0.316	24.60	-0.133	3265
2001	2007	-0.366	73.39	-0.252	26.61	-0.114	3526
2009	2012	-0.235	75.71	-0.171	24.29	-0.064	3219
2013	2016	-0.169	76.61	-0.138	23.39	-0.031	2934

* The columns $\Omega_{G,j}$ and $S_{G,j}$ with $G = \{d, exp\}$ and $j = \{1, 2\}$, denote the aggregate productivity and the aggregate sales share related to firms' domestic and export activity, measured in the initial year (Year 1) and the last year of the period (Year 2). All sales shares $S_{G,j}$ are given in %.

Chapter 3

Productivity, markups, entry, and exit: evidence from French manufacturing firms from 1994 to 2016[1]

3.1 Introduction

This chapter analyses the development of aggregate productivity and markups among French manufacturing firms between 1994 and 2016, with a special focus on the effects of firm entries and exits. For this purpose, I combine the fiscal firm-level datasets FICUS (1994-2007) and FARE (2008-2016). Further, following Ackerberg et al. (2015), I estimate a gross output translog production function to derive firm-level productivity. Firm-level markups are also estimated based on the production function, relying on the popular production approach presented by De Loecker and Warzynski (2012). Productivity and markups carry important information about the functioning of an industry. Consider first productivity. Generally, a higher level of production, either at the level of an individual firm or at the level of the economy as a whole, is usually associated with higher economic prosperity. A higher production level can be reached either by using more inputs (capital, labor, and/or materials), or by increasing the efficiency with which these inputs are transformed into output. This latter factor, which grasps changes in output that cannot be explained by changes in inputs, is usually referred to as total factor productivity. Many studies have shown that cross-country differences in output level can in large part be explained by differences in aggregate productivity (Mankiw et al., 1992; Prescott, 1998; Hall and Jones, 1999). Furthermore, increases in productivity have strong effects on the long-term growth and prosperity of an economy (Caselli, 2005). This is because productivity is linked to firms' learning process and innovative activity, which is instrumental, if not indispensable, for a sustainable growth both on

[1] This chapter is based on De Monte, E. (2021), Productivity, markups, entry, and exit: evidence from French manufacturing firms from 1994 to 2016, *BETA Working Paper, Université de Strasbourg.* (Submitted)

the micro level (firm) and on the macro level (industry or country). Further, from a welfare perspective, in a competitive environment, higher productivity decreases costs and as a result both consumers' and producers' surplus increases. Cette et al. (2017) for the period 1991-2014 and Ben Hassine (2019) for 2000-2012, study aggregate productivity evolution of the French economy and show that aggregate productivity growth has slowed down over time. I revisit these studies using a more general model for the estimation of firm-level total factor productivity.[2]

Recently, discussions around the level and changes in the markups - describing a firm's ability to set prices above its marginal costs - are widely studied again to assess the degree and the evolution of firms' market power. Contrary to productivity, a higher level of markups, i.e. market power, is associated with lower entry rates, less capital investments and less innovation (De Loecker et al., 2020; Edmond et al., 2018). Investigating aggregate markups of U.S. firms between 1960 and 2016, De Loecker et al. (2020) show that a massive increase in aggregate markups has taken place from 1980 on. They highlight that the rise in markups has been driven by high markup firms, whereas the median markup kept almost stable. They also show that the rise in markups explains the decrease in labor share and innovation arguing that this is motivated by firms cost minimizing program, where higher markups directly reduce firms demand for labor and capital investment. Less capital investments, in turn, lead to less innovation activity. In this vein, Edmond et al. (2018) show that increasing markups reduce welfare considerably. This chapter contributes to the discussion of the evolution of aggregate market power, which, to my knowledge, has not yet been done over such a long period of more than two decades using French firm-level data. Further, besides investigating the development of aggregate productivity and markups, this chapter aims to establish to what extent firm dynamics, i.e. firm entry and exit, affect both aggregate measures, by using the decomposition method presented by Melitz and Polanec (2015). Drawing on the decomposition method, this chaper also investigates reallocation effects, that is to what extent productivity and markups change with variations in firms' output shares. All else equal, higher productivity translates into higher markups (Syverson, 2019; Berry et al., 2019), which motivates the analysis of productivity along with markups.

I find that aggregate productivity in the French manufacturing industry has grown by about 48% from 1994 to 2016. The growth was primarily driven by incumbent firms' productivity improvements rather than by the market entry of high productivity firms or the market exit of low-productivity firms. Confirming the findings of Cette et al. (2017) and Ben Hassine (2019), my results reveal a slowdown in aggregate productivity growth, which is mainly induced by a slowed reallocation process of output shares among incumbents.

[2] In particular, to estimate firm-level productivity, Cette et al. (2017) use a Cobb-Douglas production function assuming constant returns to scale, and Ben Hassine (2019) use a value-added Cobb-Douglas production function. The use of a gross output translog production function in this chapter generalizes these approaches.

Further, while I find aggregate markups to vary over time, my findings cannot confirm the systematic increase in markups documented by De Loecker et al. (2020) for the U.S. economy. I show that incumbent firms maintain a considerably higher aggregate level of markups and contribute positively to the aggregate markup. The net entry contribution to overall aggregate evolution of markups reveals a varying sign, where especially entering firms considerably contribute negatively to the overall evolution toward the end of the investigated time horizon. Also, I find that high markup firms experience a decrease in markups over time which further contrasts with the findings of De Loecker et al. (2020). Analysing in a regression framework the relation between markups and various firm characteristics, I find that entering firms tend to have lower market power and/or adopt an aggressive price policy to remain in the market.

The reminder of the chapter is organized as follows. Section 3.2 reviews the relevant literature. Section 3.3 and Section 3.4 introduce the theoretical and empirical framework. Section 3.5 presents the data and descriptive statistics. Section 3.6 analyses the evolution of aggregate productivity and markups with entry and exit of firms. Section 3.7 provides insights into heterogeneity across manufacturing sectors. Section 3.8 investigates the distribution and convergence patterns of productivity and markups. Section 3.9 analyses the relation between markups and firm characteristics. Finally, Section 3.10 concludes.

3.2 Related literature

Productivity probably more than markups are vastly treated topics in the field of industrial organization. I present selected studies on that issue, which, however, by no means cover the entire body of literature.

3.2.1 Productivity

An important reason why productivity is extensively studied at the firm-level is because productivity is seen as an important determinant for firms' ability to survive in the market. Well-known industry models such as the ones presented by Jovanovic (1982), Hopenhayn (1992), and Ericson and Pakes (1995) describe the selection process of firms entering, surviving, and exiting the market to be determined by firms' productivity. In fact, Fariñas and Ruano (2005) for firms in the Spanish manufacturing and Wagner (2010) for German manufacturing firms empirically confirm the hypothesis that survivors and entrants reveal higher productivity levels compared to exiting firms. That is, a firm's productivity is crucial for its own ability to survive, and the process of entry and exits shapes the evolution of the aggregate level of productivity of a given economy or industry. The best way to measure aggregate productivity is to derive it from individual firms' productivity (Van Biesebroeck, 2008). In the literature, it is common to measure aggregate productivity by a weighted average of firm-level productivity, weighted by their market (or sales) shares. In addition, Olley and Pakes (1996) show that the weighted average can be decomposed into an unweighted average component and a covariance term between firm's productivity and their market share. That is, an increase in the aggregate measure might be induced by an increase in the average productivity or by market shares reallocation. The first term is referred to the within-change or learning effect and the second one to the between-change or reallocation effect.[3] In a dynamic setting, when firm entry and exit occurs, it is natural to investigate the impact of firm dynamics on aggregate productivity. Baily et al. (1992), Foster et al. (2001) and more recently Melitz and Polanec (2015) develop decomposition methods that allow to investigate the contribution of the firm groups of survivors, entrants, and exitors on aggregate productivity growth. While there are some differences in measuring the contribution of the firm groups on aggregate productivity growth, all methods measure the aggregate productivity by a weighted average of firm-level productivity, weighted by their market/sales shares. Most studies show that aggregate productivity growth is considerably impacted by surviving firms' within-change, i.e. by the learning effect, and less by market share reallocations and that surviving firms contribute relatively more to the aggregate productivity growth compared to entering and exiting firms. Ben Hassine (2019) applies and compares the three methods on French firm-level data. He shows that firms' (average) productivity improvement, i.e. the learning effect, mainly contributes to the aggregate productivity evolution, whereas the reallocation effect of market shares, turns out to have a minor effect on the aggregate productivity growth.

While these decomposition methods allow to investigate the efficiency of output share allocation w.r.t. aggregate productivity growth, another studies look at allocative efficiency of inputs. Restuccia and Rogerson (2008) provide a model that shows that resource allocation in an economy with heterogeneous firms in term of productivity is an important determinant for per capita output and aggregate total factor productivity. Hsieh and Klenow (2009) show that if resources were allocated as efficiently as in the U.S., aggregate productivity would increase by 30%–50% in China and 40%–60% in India. There are various studies applying the Hsieh and Klenow approach: Bellone et al. (2013) do not find such a productivity gap due to misallocation between France and the U.S. Calligaris et al. (2016) find that if the level of misalocation among Italian firms remained at the level of 1995, in 2013 aggregate productivity would be 18% higher. Ryzhenkov (2016) finds that if the Ukraine manufacturing attained the level of allocative efficiency of the U.S. or E.U., aggregate productivity could be doubled. Also see Restuccia and Rogerson (2013) for a detailed review on this topic.

[3]Section 3.6 discusses in detail the decomposition of aggregates w.r.t. within/between change as well as firm entry and exit.

Another strand of the literature focuses on the overall trend of the evolution of productivity. Recent studies have documented that productivity growth has slowed down. For instance, for the U.S. economy a productivity slowdown from the early 2000s on is measured and discussed by Decker et al. (2017), Gordon (2017), Syverson (2017) and Byrne et al. (2016). For the French economy too, Cette et al. (2017) find that productivity growth slows down from 2000 on. They relate this development to inefficient resource allocation.[4]

3.2.2 Markups

Firms that face inelastic demand are able to exert market power and set prices above marginal costs, a gap also called markups.[5] As both prices and marginal costs are mostly unobserved, markups are unobserved, too, and therefore need to be estimated econometrically. Seminal contributions to the empirical estimation of markups were provided by Hall (1986, 1988). In particular, he shows that under the assumption of cost minimizing firms, average markups can be estimated as the ratio of elasticity of output of any flexible input (an input free of adjustment costs), and the corresponding input revenue share. If this ratio is equal to one output price and marginal cost equalize and, thus, there are no markups.[6] Hall investigates markups at the 2-digit industry-level and finds (average) markups far above one, suggesting a considerable degree of market power and, thus, imperfect competition. Klette (1999) builds on the Hall-approach and finds very little (average) markups among Norwegian manufacturing firms. Likewise inspired by the Hall-approach, De Loecker (2011) and De Loecker and Warzynski (2012) develop and apply an approach, allowing to estimate markups at the firm-level. Using data from Slovenian manufacturing firms, De Loecker and Warzynski (2012) find that exporting firms reveal considerably higher level of markups compared to non-exporting firms. Bellone et al. (2016) apply their approach on data of French manufacturing firms. While confirming higher markups for exporting firms, they also find for the period 1998-2007, decreasing aggregate markups. Caselli et al. (2018) treat French firm-level data to study determinants for markdowns, i.e. when firms' prices are found to be below marginal costs. They find that markdowns are persistent and name potential candidates to explain them, such as subsidies, strategic behaviour (aggressive price policy to crowd out competitors), uncertainty, and irreversibility (difficulties to liquidate capital). De Loecker et al. (2020) explicitly focus on the evolution of aggregate markups in the U.S. economy and measure a dramatic increase between 1980 and 2016, from 21% to 61% of prices

[4]See also Bellone (2017) for a controversial discussion on that paper.

[5]A popular metric to measure the level of competition and/or market power in an economy (or industry) is the Herfindahl-Hirschman Index (HHI), which measures market share concentration. That is, the higher the concentration of firms' market shares, the lower the level of competition. De Loecker et al. (2020) highlight that the HHI has some drawbacks as it relies on a narrow definition of the underlying market, which might change over time. They therefore suggest to measure market-power, and so the level of competition, based on firm-level markups.

[6]This approach is presented and discussed more in detail in the following section.

above marginal costs. Their results show that, while the median markup remains relatively constant, the aggregate markup has been driven upwards by few high markup firms, detaining large market power. Moreover, they measure a dynamic reallocation process where market shares are allocated to high markup firm. De Loecker et al. (2018) argue that both technical innovation and change in market structure, such as the decline in antitrust enforcement, are crucial determinants for the rise in market power. Ledezma (2021) provides a theoretical model in which firms with marginal cost advantages further push them down to exploit the market size. In this model, when firm entry and exit stimulates firm selection at most, the strategic marginal cost decreasing behavior disappears, which draws the link between aggregate productivity and firm dynamics. Traina (2018) contrasts the findings by De Loecker et al. (2020) and argues that when representing public firms more accurately in the sample, aggregate markups only increase modestly. He therefore concludes that if markups have kept almost constant, macroeconomics trends, such as the increase in (market share) concentration and the decline in labor share, might rather be explained by the changing production technologies that are capital-biased, with higher economies of scale.[7] Using industry data, Hall (2018) finds increasing markups between 1988 and 2015. These changes, however, are shown to be statistically insignificant. Edmond et al. (2018) focus on the welfare costs induced by markups and show that these costs are transmitted as markups behave similar to an output tax as well as due to misallocation of input factors implied by markups. For detailed reviews, see Syverson (2019) and Berry et al. (2019), summarizing the literature w.r.t. the measurement of markups and market power and their macroeconomic implications.

3.3 Theoretical background

Consider a given industry with N firms, indexed by n at a specific point in time t. Firms transform inputs into output, described by the following Hicks neutral production function

$$Y_{nt} = F(X_{nt}^V, X_{nt}^F, \Omega_{nt}), \tag{3.1}$$

where X_{nt}^V and X_{nt}^F denote, for simplicity, one *variable* and one *fixed* input factor, and Ω_{nt} is related to total factor productivity (TFP). *Variable* inputs, such as materials, might be *adjusted* at t, whereas *fixed* inputs, such as capital, are assumed to be *predetermined*, i.e. optimally chosen by the firm prior to t.

In the field of industrial organization, production functions are extensively employed to study firms' production behavior. For instance, from production functions output elasticities w.r.t. different inputs can be derived and studied, as well as firm-level productivity that is

[7] Note that Traina (2018) refers to an earlier working paper version of De Loecker et al. (2020).

widely employed for efficiency analysis. Moreover, De Loecker (2011) and De Loecker and Warzynski (2012) provide a methodology, the so called production-approach, to derive firm-level markups from the production function.[8] Here, markups are defined as firms' ability to set prices over marginal costs, which can be interpreted as a measure of market power. More precisely, they assume firms to behave cost minimizing, which yields the objective Lagrangian function, given by

$$\mathcal{L}\left(X_{nt}^{V}, X_{nt}^{F}, \lambda_{nt}\right) = P_{nt}^{V} X_{nt}^{V} + P_{nt}^{F} X_{nt}^{F} - \lambda_{nt}\left(Y_{nt} - F(\cdot)\right), \tag{3.2}$$

where P_{nt}^{V} and P_{nt}^{F} denote the prices for the variable and fixed inputs. λ_{nt} represents the shadow price, i.e. the change in costs if the production level changes by one unit, in other words, the marginal cost of a change in output. $F(\cdot)$ represents the production technology from (3.1). The first order conditions (FOC) yield

$$\frac{\partial \mathcal{L}}{\partial X_{nt}^{V}} = P_{it}^{V} - \lambda_{nt}\frac{\partial F(\cdot)}{\partial X_{nt}^{V}} = 0. \tag{3.3}$$

The last expression can also be written by

$$\theta_{nt}^{V} = \frac{\partial F(\cdot)}{\partial X_{nt}^{V}}\frac{X_{nt}^{V}}{Y_{nt}} = \frac{1}{\lambda_{nt}}\frac{P_{nt}^{V} X_{nt}^{V}}{Y_{nt}}, \tag{3.4}$$

where θ_{nt}^{V} is the output elasticity w.r.t. the variable input. Defining the markup by $\mu_{nt} = P_{nt}/\lambda_{nt}$, i.e. output price over marginal cost, and insert the expression into the previous equation, we obtain an expression for the markup by

$$\theta_{nt}^{V} = \frac{\mu_{nt}}{P_{nt}}\frac{P_{nt}^{V} X_{nt}^{V}}{Y_{nt}} \Longleftrightarrow \mu_{nt} = \frac{\theta_{nt}^{V}}{a_{nt}^{V}}, \tag{3.5}$$

where $a_{nt}^{V} = (P_{nt}^{V} X_{nt}^{V})/(P_{nt} Y_{nt})$ denotes the output share of the variable input. That is, a firm's markup is measured by the ratio of output elasticity w.r.t. the variable input and the according input share.

[8] As already mentioned in the previous section, this approach strongly relies on Hall (1986, 1988).

3.4 Empirical framework

3.4.1 Production function estimation

Empirically, I approximate the production function from equation (3.1) by a gross output translog (TL) production function, given by

$$y_{nt} = \alpha_0 + \sum_i \alpha_i x^i_{nt} + \frac{1}{2}\sum_{ij} \alpha_{ij} x^i_{nt} x^j_{nt} + \omega_{nt} + \epsilon_{nt}, \tag{3.6}$$

lower case letters denote logs, where gross output production is supposed to be given by $y_{nt} = \log(Y_{nt}) + \epsilon_{nt}$, and x^i_{nt} with $i = (k, l, m)$ denotes the input factors capital, labor, and intermediary products (materials), ω_{nt} represents the log-level of TFP, and ϵ_{nt} an *iid* shock.[9] TFP is unobserved by the econometrician and as such a residual of the production function. However, its decomposition from ϵ_{nt} is made since TFP is assumed to be known or anticipated by the firm prior to t and, hence, potentially contributes to the firm's decisions about input quantities. Instead ϵ_{nt} is only observed by the firm ex-post, i.e. after t, and supposed to be uncorrelated with the input decisions. As common in the production function literature, I suppose that firms' capital stock evolves according to $K_{nt} = \kappa(K_{n,t-1}, I_{nt})$, where $K_{nt} = \exp\left(x^k_{nt}\right)$ and I_{nt} denotes a firm's amount of investments. Moreover, since the French labor market is relatively regulated, I consider labor input as fixed. This timing assumption implies that capital and labor is chosen by the firms prior to observing their productivity ω_{nt}. Instead, materials are supposed to be flexible, and hence adjustable w.r.t. ω_{nt}. As extensively discussed in many studies such as Olley and Pakes (1996) (OP, henceforth), Levinsohn and Petrin (2003) (LP), Ackerberg et al. (2015) (ACF) and Wooldridge (2009) a crucial difficulty to deal with when estimating production functions consists in the endogeneity of the explanatory variables, arising when a firm chooses its flexible inputs (here x^m_{nt}) as a function of the productivity shocks ω_{nt}. This is also known as the simultaneity bias, which OP propose to circumvent by a two stage estimator, using firm investments as proxy variable to control for unobserved productivity. The LP approach suggests to use materials as a proxy since firm investments take frequently zero values. I will estimate the production function presented in equation (3.6) in the LP spirit and proceed very similar to ACF.[10] The identification strategy of the production function parameters is briefly presented in the following. In the first stage a scalar observable is used to control for the unobserved productivity. As proxy variable the flexible input factor materials is used, which is supposed to be generated as a function of capital and labor input as well as the unobserved productivity, expressed by $x^m_{nt} = h(x^k_{nt}, x^l_{nt}, \omega_{nt}, c_{nt})$, where c_{nt} contains control variables such as a dummy variable for firm exit, 4-digits sector, and time dummies. The key assumption in the first step is the

[9] That is, gross output production is allowed to contain measurement errors that are, along with unanticipated shocks to production, comprised in ϵ_{nt} (De Loecker and Warzynski, 2012).

[10] Also see De Loecker and Warzynski (2012) for a further application.

assumption of strict monotonicity of x^m_{nt} in ω_{nt}. This assumption implies invertibility of h in ω_{nt}, yielding $\omega_{nt} = h^{-1}(x^k_{nt}, x^l_{nt}, x^m_{nt}, c_{nt})$, which is then substituted into equation (3.6) to obtain

$$\begin{aligned} y_{nt} &= \alpha_0 + \sum_i \alpha_i x^i_{nt} + \frac{1}{2}\sum_{ij} \alpha_{ij} x^i_{nt} x^j_{nt} + h^{-1}(x^k_{nt}, x^l_{nt}, x^m_{nt}, c_{nt}) + \epsilon_{nt} \\ &= f(x^k_{nt}, x^l_{nt}, x^m_{nt}, c_{nt}) + \epsilon_{nt}. \end{aligned} \tag{3.7}$$

I approximate $f(\cdot)$ by a fourth order polynomial in inputs and add other control variables contained in c_{nt}. That is, the first stage yields the estimate $\widehat{f}(x^k_{nt}, x^l_{nt}, x^m_{nt}, c_{nt})$, which is used in the second stage to accomplish the identification of the parameters of interest. For the second stage, the second key assumption lies on the law of motion of ω_{nt}, which is assumed to be a first order Markov process, where firm entry and exit is allowed to impact the productivity, i.e.

$$\omega_{nt} = g\left(\omega_{n,t-1}, e^-_{nt}\right) + \xi_{nt}, \tag{3.8}$$

where $g(\cdot)$ defines the productivity process, $e^-_{nt} = 1$ if a firms exits in the subsequent period and zero else, which is included to control for self-selected exit (Olley and Pakes, 1996), and ξ_{nt} is an *iid* error term with $E(\xi_{nt}|\omega_{n,t-1}, e^-_{nt}) = 0$. [11] From equation (3.7) it follows that

$$\widehat{\alpha_0 + \omega}_{nt}(\alpha) = \widehat{f}(x^k_{nt}, x^l_{nt}, x^m_{nt}, c_{nt}) - \sum_i \alpha_i x^i_{nt} + \frac{1}{2}\sum_{ij} \alpha_{ij} x^i_{nt} x^j_{nt}, \tag{3.9}$$

where $\alpha = (\alpha_i, \alpha_{ij})$ with $i = \{k, l, m\}$. The innovations in ω_{nt}, namely $\widehat{\xi}_{nt}$, are obtained by regressing $\widehat{\alpha_0 + \omega}_{nt}(\alpha)$ on a higher order polynomial of $\widehat{\alpha_0 + \omega}_{n,t-1}(\alpha)$ along with the exit dummy. Then, for some initial values for the parameters, α can be estimated by a search over the space of the parameters in α, imposing the moment conditions[12,13]

[11] See Appendix 3.11.2 for the definition of firm exit.

[12] The choice of the instruments in the moment equation (3.10) is related to the timing assumption mentioned above. Since I suppose that firms chose both capital and labor input at $t-1$, whereas the flexible input materials is supposed to be chosen at t, I use the instruments x^k_{nt}, x^l_{nt}, and $x^m_{n,t-1}$ (as well as higher orders and combinations of them), that should be orthogonal to the shocks in innovation, given by ξ_{nt}.

[13] As initial values I use the estimated coefficients of an OLS regression of y_{nt} on all variables of the gross output production function.

$$E\left[\widehat{\xi}_{nt}(\alpha)\begin{pmatrix} x^k_{nt} \\ x^l_{nt} \\ x^m_{n,t-1} \\ (x^k_{nt})^2 \\ (x^l_{nt})^2 \\ (x^m_{n,t-1})^2 \\ x^l_{nt}x^k_{nt} \\ x^m_{n,t-1}x^k_{nt} \\ x^m_{n,t-1}x^l_{n,} \end{pmatrix}\right] = 0. \tag{3.10}$$

Note that the moment conditions are derived from the first order Markov assumption (given in equation (3.8)), implying orthogonality between the production input factors and the innovation to productivity, ξ_{nt}.

I rewrite these conditions more parsimoniously as

$$E\left[d(\alpha, x_{nt})\right] = 0, \tag{3.11}$$

where $d(\cdot)$ represents a $L \times 1$ vector of moment conditions with $L \geq J$, where J is the total number of parameters to be estimated, and x_{nt} the data (all endogenous and exogenous variables). Using 2-step GMM (Hansen, 1982), the parameters of interest can be estimated by

$$\widehat{\alpha} = \arg\min_{\alpha} \overline{d}(\alpha)' W \overline{d}(\alpha), \tag{3.12}$$

where W is a $L \times L$ optimal weighting matrix, given by the inverse of the covariance matrix of $d(\alpha, x_{nt})$,[14] and

$$\overline{d}(\alpha) = \frac{1}{N}\sum_{n=1}^{N}\frac{1}{T_n}\sum_{t=1}^{T_n} d(\alpha, x_{nt}), \tag{3.13}$$

with T_n an individual firm's total number of observations.

After obtaining consistent estimates of the production function parameters, firms' productivity is recovered by

$$\widehat{\omega}_{nt} = y_{nt} - \sum_i \widehat{\alpha}_i x^i_{nt} + \frac{1}{2}\sum_{ij}\widehat{\alpha}_{ij} x^i_{nt} x^j_{nt} - \widehat{\epsilon}_{nt}, \tag{3.14}$$

where $\widehat{\epsilon}_{nt} = y_{nt} - \widehat{f}(x^k_{nt}, x^l_{nt}, x^m_{nt}, c_{nt})$.

[14] Here, the covariance matrix of $d(\alpha, x_{nt})$ is estimated in a first step, using (3.12) by setting W to the $L \times L$ identity matrix.

3.4.2 Firm-level markups

According to equation (3.5), markups can be estimated by the ratio of the output elasticity w.r.t. the variable input materials and its input share, given by

$$\widehat{\mu}_{nt} = \frac{\widehat{\theta}^M_{nt}}{\widehat{a}^M_{nt}}, \tag{3.15}$$

where the output elasticity w.r.t materials, $\widehat{\theta}^M_{nt}$, is obtained by[15]

$$\widehat{\theta}^M_{nt} = \frac{\partial y_{nt}}{\partial x^i_{nt}} = \widehat{\alpha}_m + \widehat{\alpha}_{mm} x^m_{nt} + \widehat{\alpha}_{km} x^k_{nt} + \widehat{\alpha}_{lm} x^l_{nt}. \tag{3.16}$$

The input share of materials, generally expressed by $a^M_{nt} = (P^M_{nt} M_{nt})/(P_{nt} Y_{nt})$, can be directly obtained from the data. However, since we do not observe Y_{nt} but $\tilde{Y}_{nt} = Y_{nt} \exp(\epsilon_{nt})$, where ϵ_{nt} is the error from the regression equation (3.7), De Loecker and Warzynski (2012) propose to correct and estimate the input share by

$$\widehat{a}^M_{nt} = \frac{P^M_{nt} M_{nt}}{P_{nt} \frac{\tilde{Y}_{nt}}{\exp(\widehat{\epsilon}_{nt})}}. \tag{3.17}$$

3.4.3 Discussion

Obviously, the crux of estimating firm-level productivity and markups is the specification and estimation of the production function. In the literature, the most applied production function specification is the Hicks-neutral Cobb-Douglas (CD) production function (Bellone, 2017; Traina, 2018; Ben Hassine, 2019). De Loecker et al. (2020) also employ a Cobb-Douglas (CD) specification, however, with time-varying coefficients, for a given 2-digit industry. In particular, De Loecker et al. (2020) use a five-year rolling window around the year at which the production function is estimated. That is, their specification allows for a flexible production technology over time. Even though, such a specification is likely to suffer from misspecification by neglecting higher order polynomials, i.e. neglecting non-linearity in the data. The main motivation why I use a TL specification is to allow for more flexibility compared to the CD specification, allowing to relax the assumption of constant output elasticities. However, I suppose that the time varying component of the technology is fully encompassed by the additive technological change term ω_{nt}, as the production function coefficients are not time-varying. That is, firm-level elasticity only changes through a change in the firm's input mix but not through changing technology parameters. Generally, there are two ways to take the time dimension into account: First, rolling-window estimation, second modelling the

[15] The output elasticity w.r.t. the other inputs capital and labor can be obtained analogously. Firms' returns to scale is then obtained by taking the sum of all output elasticities, i.e. $\widehat{RS}_{nt} = \widehat{\theta}^K_{nt} + \widehat{\theta}^L_{nt} + \widehat{\theta}^M_{nt}$.

time trend explicitly. Rolling window estimation has the drawback that not all periods can be used, which I see as a larger disadvantage in my case (see Zanin and Marra (2012) for a discussion on rolling window estimation). The second option, to model the time trend, adds a considerable number of parameters which is numerically burdensome to be estimated as the TL production function already includes a relatively high number of parameters. Generally, assuming any parametric functional form of the production function might suffer from misspecification. To prevent from such model misspecification, novel techniques to estimate the production function nonparametrically, such as developed by Gandhi et al. (2020) and Demirer (2020), would certainly improve and generalize my approach. In this vein, Demirer (2020) argues that assuming a Hicks-neutral production function, i.e. implying no unobserved heterogeneity in firms' output elasticity, also leads to biased estimates, which, as he illustrates, considerably translates into biased estimates of firms' markup. Demirer (2020), therefore, suggests to employ a non-neutral (factor-augmented) production technology.[16] Morlacco (2017) argues to focus as base-line model on the CD production function, as a TL specification leads to outliers in the markup measures, distorting further analysis. To handle this issue on outliers in the markup measures, I winsorize the distribution of markups at the $1th$ and $99th$ percentile, which already eliminates important outliers (Hastings et al., 1947).

Concerning the choice of materials as flexible input, in the most applications of the production approach to measure firm-level markups, labor is used as flexible input. Generally, the decision about which input can be viewed as flexible or fixed should adapt to the specific economic context. Here, considering labor beside capital as fixed input, is, in my view, more appropriate to the French labor market characteristics. This leaves only materials as a flexible input, which I use for the estimation of markups.[17]

A limit of my approach is that I only have access to firm-level revenue (output) and expenditure (inputs) data, which is deflated by 2-digit price indices. That is, price variations among firms in both output and inputs are not taken into account. However, if price differences in output and input markets are correlated with the optimal choice of firms' output and input, the estimated coefficients of the production function suffer from the output/input price bias. This is likely to be the case in industries that reveal imperfect competition. Foster et al. (2008), De Loecker et al. (2016), and Morlacco (2017) discuss this concern in detail and provide approaches to circumvent the output/input price bias.

[16] See Doraszelski and Jaumandreu (2018) and Chen (2017) for more discussions on non-neutral production functions and their estimation.

[17] It is noteworthy to mention that even in markets in which both labor and materials could be considered as flexible inputs, using either labor or materials for the estimation of markups leads to substantially different outcomes (Raval, 2019).

3.5 Data and descriptive statistics

3.5.1 Data

I analyse French firm-level data where I combine the (fiscal) datasets FICUS and FARE covering the periods 1994-2007 and 2008-2016, respectively.[18] The datasets contain detailed information about firms' reports in balance sheets and income statements. Note that, in 2008 the French institute for statistics (INSEE) made significant changes w.r.t. the industrial sector nomenclature firms belong to. In both datasets, the principal sector identifier is at the 4-digit level, where in FICUS sectors were differently labelled compared to FARE.[19] In order to guarantee consistency in the sector nomenclature I manage to use throughout the whole period, 1994-2016, the same sector nomenclature. This is especially important since I aim to estimate the production function at the 2-digit level and so consistency in the sector nomenclature is required. See Chapter 2, Appendix 2.9 for a more detailed description of the construction of the dataset. I only keep those firms with at least five employees to prevent estimates to be distorted by a large fraction of very small firms, likely to contain measurement errors. Furthermore, motivated by the fact that I estimate a TL production function, I only keep those firms that report positive values for sales, capital and materials. The final dataset includes 19 2-digit manufacturing sectors, containing for the period 1994-2016 96,013 firms, summing up to 851,261 observations. Table 3.1 provides a description of the considered 2-digit sectors and the corresponding number of firms/observations. Note that some manufacturing sectors are excluded: 10 (manufacture of food products), 12 (manufacture of tobacco products), and 19 (manufacture of coke and refined petroleum products). Sector 10 is excluded for its untypical structure, i.e. a very large amount of very small firms, strongly influencing the aggregate measure. The sectors 12 and 19, instead, are excluded by reason of a low number of observations.

[18] FICUS and FARE refer to "fichier de comptabilité unifié dans SUSE" and "fichier approché des résultats d'Esane", respectively. That is, FICUS was part of the French firm-level database SUSE. In 2008, FICUS was replaced by FARE, which, in turn, belongs to the database Esane.

[19] In particular, in FICUS and FARE industrial sectors are classified according to NAF révision 1 and NAF révision 2, respectively, where NAF refers to the French industry classification ("nomenclature d'activités françaises").

Table 3.1: Description of 2-digit manufacturing sectors

Sector*	Description	# Firms	# Obs.
11	Manufacture of beverages	1,593	15,023
13	Manufacture of textiles	4,128	37,000
14	Manufacture of wearing apparel	7,295	42,244
15	Manufacture of leather and related products	1,611	12,571
16	Manufacture of wood and of products of wood and cork	6,609	59,224
17	Manufacture of paper and paper products	2,155	22,533
18	Printing and reproduction of recorded media	9,353	78,577
20	Manufacture of chemicals and chemical products	3,491	33,180
21	Manufacture of basic pharmaceutical products/preparations	745	6,820
22	Manufacture of rubber and plastic products	6,233	63,375
23	Manufacture of other non-metallic mineral products	5,763	49,739
24	Manufacture of basic metals	1,557	14,848
25	Manufacture of fabricated metal products	22,165	219,412
26	Manufacture of computer, electronic and optical products	4,144	32,243
27	Manufacture of electrical equipment	3,077	27,345
28	Manufacture of machinery and equipment n.e.c.	7,612	66,925
29	Manufacture of motor vehicles, trailers and semi-trailers	2,528	23,684
30	Manufacture of other transport equipment	975	7,883
31	Manufacture of furniture	4,979	38,635
Total		96,013	851,261

* Statistical classification of economic activities in the European Community, Rev. 2 (2008)

Since my prior interest is to estimate a production function, I describe in the following the required variables for this purpose. Beginning with firms' gross output I use as proxy firms' sales. Furthermore, I use firms' tangible assets reported in their balance sheets to proxy the capital stock. Labor is measured by the number of full-time employees and materials by the expenditures for raw materials. All monetary variables are deflated by the corresponding 2-digit sector price index.[20] Concerning the measurement of firm entry and exit, generally, as I use fiscal data, firms' report on their balance and income statement is mandatory. However, I also observe some non-report, especially for very small firms. Hence, the number of firms varies in the data through non-report, ambiguous firm status (temporal inactivity), and firm entry and exit. Unfortunately, it is not definitely possible to distinguish between non-report, temporal inactivity, and firm exit in a legal sense. Firms' status (survival, entry, and exit) is, therefore, only measured based on their appearance/disappearance in the data. The definition of firm status is further discussed in Section 3.6 as well as in Appendix 3.11.2.

[20]The sectoral price data are available at https://www.insee.fr/fr/statistiques/2832666?sommaire=2832834, (April, 2021).

3.5.2 Descriptive statistics

To provide an insight into the data, Table 3.2 shows the distribution of some variables w.r.t. firm size. All figures represent averages over the whole period 1994-2016. The first column contains different firm size groups, measured by the number of employees. The table shows that the share of firms in the sample is decreasing in firm size. More precisely, the largest share of firms is represented by the group of firms detaining between five and nine employees, given by 33.53%. The smallest share is represented by firms reporting 500 employees and more, given by only 1.61%. Instead, considering the shares of employees and sales, represented by the different firm size groups, it can be seen that both variables are increasing in firm size group. Here firms with five to nine employees detain only 3.75 % of total labor force (2.15% of total sales), whereas the biggest firm size group detains 42.75% of total labor (54.56% of total sales). Also, as expected, entry and exit rates are decreasing in firm size, where the smallest firm size group reveals the highest entry/exit rates.[21]

Table 3.2: Summary statistics w.r.t. firm size : averages from 1994-2016[a,b]

Size group[c]	# of firms	Share of firms	Share of empl.	Share of sales	Entry rate	Exit rate	Age
5-9	11893	33.53	3.75	2.15	5.51	5.27	17.03
10-19	8844	24.94	5.63	3.41	4.49	4.89	19.89
20-49	8537	24.07	12.50	9.00	3.36	3.75	23.09
50-99	2805	7.91	9.04	6.91	3.04	3.63	25.90
100-199	1719	4.85	11.04	9.35	2.84	3.33	27.20
200-499	1098	3.10	15.29	14.61	2.57	2.99	27.63
500+	570	1.61	42.75	54.56	3.24	2.97	29.19
Total	35466	100.00	100.00	100.00	4.29	4.48	20.92

[a] All figures represent averages over the whole period 1994-2016.
[b] Shares and rates are given in %.
[c] Size group is given in terms of number of employees.

Figure 3.1 shows the evolution of aggregate production and inputs. Here, aggregates are measured by the sum of the respective variable over all firms, where the initial year 1994 represents 100. The figure shows that the aggregate use of capital has increased steadily, reaching at 2016 186.5 w.r.t. the level of 1994. Aggregate gross output, closely followed by aggregate material input, represented by the solid and dotted line, respectively, increases until 2007 whereupon a quite dramatic drop is observed. Only from 2009 on the aggregate of both variables increases, reaching a level of 150.8 and 138.7 w.r.t. 1994. The aggregate use of labor, instead, has decreased relatively continuously form 2002 on, accounting at 2016 only 76.9.

[21]See Appendix 3.11.1 for a similar table w.r.t. the 2-digit sectors instead of firm size.

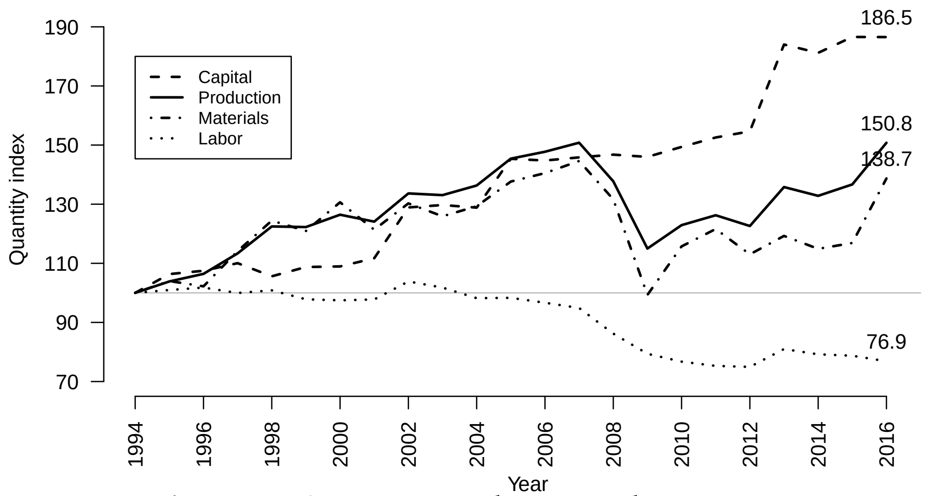

Figure 3.1: Aggregate production and inputs over time

Finally, Figure 3.2 present firm dynamics, i.e. the evolution of the number of firms along with the entry and exit rate. The upper line represents the number of firms, with the corresponding *y*-axis on the left. The figure shows that from 2002 on the number of firms is substantially decreasing reaching in 2016 a level of only about 77% compared to 1994, which translates into a yearly average growth rate of -1.12%. The evolution of the number of active firms is also reflected in the entry and exit rate, with the corresponding *y*-axis on the right: While at the beginning of the sample period entry and exit rates are higher and oscillating at a similar level, from around 2002 on, the exit rate lies above the entry rate.[22]

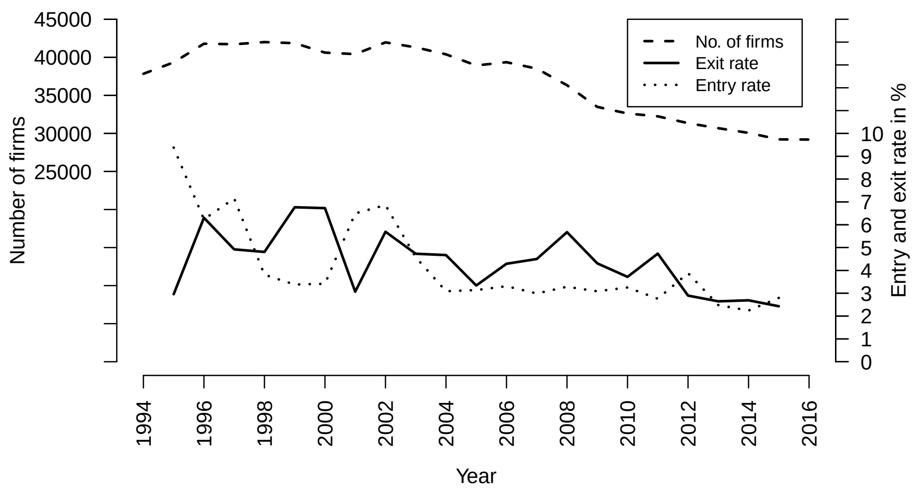

Figure 3.2: Number of firms, entry, and exit rate over time

[22]See Appendix 3.11.2 for a detailed description of the measurement of firm entry and exit on a yearly basis.

3.6 Decomposing aggregate productivity and markups with entry and exit

In this section I investigate the evolution of both aggregate productivity and markups with entry and exit. Aggregates are built on firm-level productivity and markup, obtained from the estimation of the TL production function presented above. See Appendix 3.12 for results on parameter estimates, output elasticities, and returns to scales. The productivity decomposition literature provides various methods to decompose aggregates. I apply the Dynamic Olley-Pakes Productivity Decomposition Melitz and Polanec (2015) (DOPD, henceforth), on both aggregate productivity and markup, which I briefly introduce in the following. Empirical results are presented subsequently.

3.6.1 Decomposition approach

Aggregates of either firm-level productivity or markups are measured by a weighted average of individual firms' productivity/markups, weighted by a context-specific share, such as firms' sales shares. In the context of measuring aggregate productivity, Olley and Pakes (1996) show that the aggregate might increase either by changes in individual firms' productivity/markup or by changing sales shares. More formally, let ϕ_{nt} represent an individual firm's productivity/markup measure at t and let s_{nt} denote a firm's sales share. The aggregate measure Φ_t is then given by

$$\Phi_t = \sum_{n}^{N_t} s_{nt}\phi_{nt} = \overline{\phi}_t + \sum_{n}^{N_t} \left(s_{nt} - \overline{s}_t\right)\left(\phi_{nt} - \overline{\phi}_t\right). \tag{3.18}$$

The first equality simply defines the aggregate measure as a weighted average. The second equality decomposes the weighted average into an unweighted average, $\overline{\phi}_t$, and a covariance term between firms' productivity/markup and the sales share. Aggregate growth between two periods is obtained taking the first difference, i.e. $\Delta\Phi = \Phi_t - \Phi_{t-k}$. Aggregate growth is, hence, transmitted by two reasons: (i) if firms' unweighted average changes, called the *within change*, and (ii) if the covariance between productivity/markups and sales share changes, called the *between change* - also referred to the process of reallocation of sales shares w.r.t. firms' productivity. Melitz and Polanec (2015) extend the Olley-Pakes decomposition taking into account firm entry and exit. They show that, in this case, the aggregate growth can be separated into the contribution of the three firm groups of surivors, entrants and exitors, given by

$$\begin{aligned}\Delta\Phi &= \underbrace{(\Phi_{S,t} - \Phi_{S,t-k})}_{\text{Survivors}} + \underbrace{S_{E,t}(\Phi_{E,t} - \Phi_{S,t})}_{\text{Entrants}} + \underbrace{S_{X,t-k}(\Phi_{S,t-k} - \Phi_{X,t-k})}_{\text{Exitors}} \\ &= \Delta\overline{\phi}_S + \Delta N_S cov_S + S_{E,t}(\Phi_{E,t} - \Phi_{S,t}) + S_{X,t-k}(\Phi_{S,t-k} - \Phi_{X,t-k}),\end{aligned} \tag{3.19}$$

where $S_{Gt} = \sum_{n \in G} s_{nt}$ denotes the aggregate sales share of a group G with $G = (E, S, X)$ the indexes referred to the group of entrants, survivors, and exitors. In the the second equality, the first and the second term represent the within and between change component. That is, the sum of both terms describes the contribution of surviving firms to aggregate productivity growth, whereas the last two terms describe the contribution of the group of entrants and exitors, respectively, to aggregate productivity growth. The DOPD method implies that the aggregate measure of the group of surviving firms states for all groups the reference level. That is, the group of surviving firms contribute positively to aggregate productivity growth if their aggregate productivity at t is higher compared to that group's aggregate measure at $t-k$, i.e. $\Phi_{S,t} - \Phi_{S,t-k} > 0$. The group of entering (exiting) firms contributes positively to the aggregate's growth if their aggregate measure is higher (lower) compared to one of the group of surviving firms at t $(t-1)$, i.e. $\Phi_{E,t} - \Phi_{S,t} > 0$ $(\Phi_{S,t-k} - \Phi_{X,t-k} > 0)$. [23]

Defining firm survival, entry, and exit

In the framework of the productivity decomposition I aim to assign the contribution of the groups of surviving, entering, and exiting firms to aggregate productivity growth for periods longer than one year. That is, I hear consider an initial year, $t-k = 1994$, and let t vary to cover each year in the period at which growth of either productivity or markup is decomposed into the contribution of the different groups. For this purpose, a firm is identified as a survivor if the firm is active at both the initial period, $t-k$, and at respective year, t. A firm is defined as an entrant if it is not active at $t-k$ but active at t. Likewise, a firm is defined as and exitor if it is active at $t-k$ but inactive at t. Note that a small share of firms enters and exits more than once. However, the longer the time span becomes, the more accurately the survival/entry/exit measure reflects a firms' actual status. A potential bias from incorrect measure of firms' status should therefore reduce the longer the time span becomes.

Discussion

In the productivity decomposition literature there exist other similar methods measuring aggregate productivity with firm entry and exit, notably the ones presented by Griliches and Regev (1995) and Foster et al. (2001). Melitz and Polanec (2015) discuss and compare these methods in detail arguing that their decomposition more accurately reflects the contribution of each firm group. Further, when measuring aggregate markups, De Loecker et al. (2020) point to the fact that the choice of the weight in use matters. They compare sales shares and total cost shares but focus on the first one for three reasons: First, sales dynamics are mainly affected by reallocation of revenues to high-markup firms, which could be captured using input weights. Second, markups are linked to profit-rates, which are also weighted by revenue shares, which, therefore, establishes consistency in their framework. Edmond

[23] See Appendix 3.13.1 for more details on the derivation of the DOPD approach.

et al. (2018) argue that cost share weighting better reflects distortions to employment and investment decisions. I compare sales and cost weighting as robustness check in Appendix 3.14.3, and show that both methods produce very similar patterns.

3.6.2 Empirical decomposition of aggregate productivity

The DOPD presented in equation (3.19) is applied on all firms in the sample, with the initial year given by 1994. The contributions to the change in aggregate productivity of each component, i.e. from the groups of surviving firms and net entry, are added cumulatively throughout the years until 2016. Figure 3.3 provides the results of this exercise. Consider first the total aggregate (log) productivity growth, represented by the solid line. From 1994 to 2016 the aggregate productivity is continuously increasing. For that period I measure that aggregate productivity has grown by about 48%, representing annual average growth rate (AGR) of about 1.8%. However, the AGR is decreasing over time: While I measure from 1994 until the year 2000 an AGR of 3.2%, for 2001 until 2016 I only measure an AGR of about 1.5%. This provides further empirical evidence for a slowdown in aggregate productivity growth, confirming Cette et al. (2017) who likewise document a slowdown in aggregate productivity growth for the French economy from 2000 on. Bellone et al. (2016) find a similar pattern for aggregate productivity evolution for the period 1998-2007.

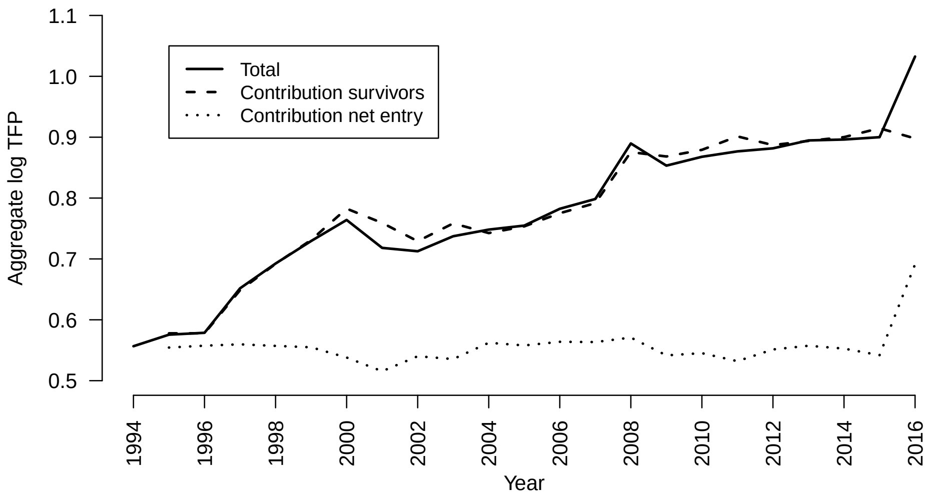

Figure 3.3: Aggregate log productivity decomposition with entry and exit

The contribution of the group of survivors and net entry are represented by the dashed and dotted line, respectively. It can be seen that surviving firms contribute the overwhelming share to the total aggregate productivity evolution as the dashed line very closely follows the dotted line. Instead, the contribution of net entry is very low, where the positive entry effect is almost compensated by the negative exit effect. In particular, the contribution of entering firms to aggregate productivity growth is often positive which indicates that at the aggregate, the group of entering firms has a higher level of productivity compared to surviving firms. On the other side, the contribution of exiting firms, showing most of the years a negative sign, implies that relatively productive firms have left the market from 1994 until the respective year. Further, Figure 3.4 allows insights into learning and reallocation effects among surviving firms. Here, the contribution of surviving firms' to aggregate productivity is further decomposed into the contribution through the unweighted productivity, i.e. the within-change (learning effect) and the between-change, i.e. reallocation effects. The figure shows that surviving firms' within-change (dotted-dashed line) exhibits the same tendency as that group's the total aggregate productivity evolution (see the dashed and solid line, respectively). This indicates that the within-change contribution of surviving firms accounts for a very large part of the overall evolution. The between-change contribution, indicated by the bottom line (long-dashed line), shows a strong impact until the year 2000, implying that productivity growth was mainly contributed by positive reallocation effects, where sales shares shifted from lower to higher productive firms. After 2000 I measure a drop in these dynamics whereupon no considerable reallocation takes place. This indicates that the slowdown in productivity from 2000 is mainly due to a slowed reallocation process and less due to firms' learning process. On average over the whole period, within- and between-change accounts for about 69% and 31% of surviving firms' productivity improvement.[24] The finding that the within contribution of surviving firms is an important driver for aggregate productivity evolution, and that net entry contribution plays a relatively smaller role compared to surviving firms' contribution, goes in line with other studies in the literature (Melitz and Polanec, 2015; Baily et al., 1992; Foster et al., 2001; Ben Hassine, 2019).

Appendix 3.14.2 compares aggregate productivity obtained from the TL production function with aggregate productivity obtained from the Cobb-Douglas (CD) production function. Results yield similar qualitative patterns for both specifications. However, as Table 3.6 in Appendix 3.12 illustrates, the parameter estimates belonging to higher order polynomials of the TL production function are, for many sectors, statistically significant, indicating that the CD specification suffers from misspecification.

[24] See Appendix 3.13.2, Table 3.8 for the exact measures of the decomposition, i.e. the respective group's aggregate productivity and sales shares as well as their contributions to aggregate productivity growth.

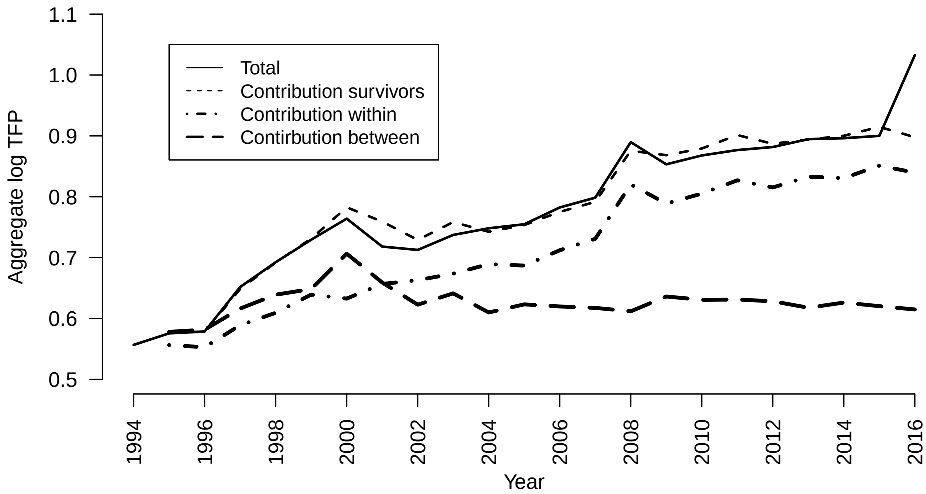

Figure 3.4: Aggregate log productivity decomposition with entry and exit

3.6.3 Empirical decomposition of aggregate markups

The decomposition of aggregate markups is conducted analogously to the one for aggregate productivity. Figure 3.5 illustrates the evolution of aggregate markup with the contribution of the group of surviving firms and the contribution of net entry. The overall aggregate markup, shown by the solid line, experiences between 1994 and 1998 an increase whereupon I measure a relative continuing decrease until 2005. After a sharp increase between 2007 and 2009, I measure again a decline, with a relatively stable aggregate markup from 2011 until 2015, and a drop for the very last year of the sample period. More precisely, in 1994 I measure a total aggregate markup of 1.16, that is prices are on average about 16% higher compared to marginal costs. The highest measured aggregate markup in 2009 is given by about 1.32, declining in 2015 (2016) to about 1.24 (1.15).[25] Generally, for the French manufacturing, I find relatively stable aggregate markups, which contrasts the finding of a systematic increase for the U.S. economy (De Loecker et al., 2020). For almost all periods, the group of surviving firms (dashed line) contributes positively to the aggregate evolution. The sign of the contribution of net entry (dotted line), instead, changes: While exiting firms mostly contribute positively to aggregate markups, i.e. firms that shut-down between 1994 and the respective year reveal a smaller aggregate markup compared to the aggregate markup of surviving firms, the group of entering firms contributes mostly negatively to the aggregate markup (especially towards the end of the sample period). That is, in the latter case, new entering firms have at the aggregate a smaller markup compared to the group

[25] Also see Bellone et al. (2016) who find for the French manufacturing a similar pattern of decreasing markups for the period 1998-2007.

of surviving firms. Therefore, the net entry effect becomes negative, which can be seen as the total aggregate markup lies between the one of surviving firms and net entry (from 2005-2007 and 2010-2016). On average, surviving firms lead to an increase in the markup of 6.7 percentage points, compared to 1994. Instead, the group of entering and exiting firms contribute to the total aggregate markup on average with -4.5 and 4.1 percentage points, respectively.[26]

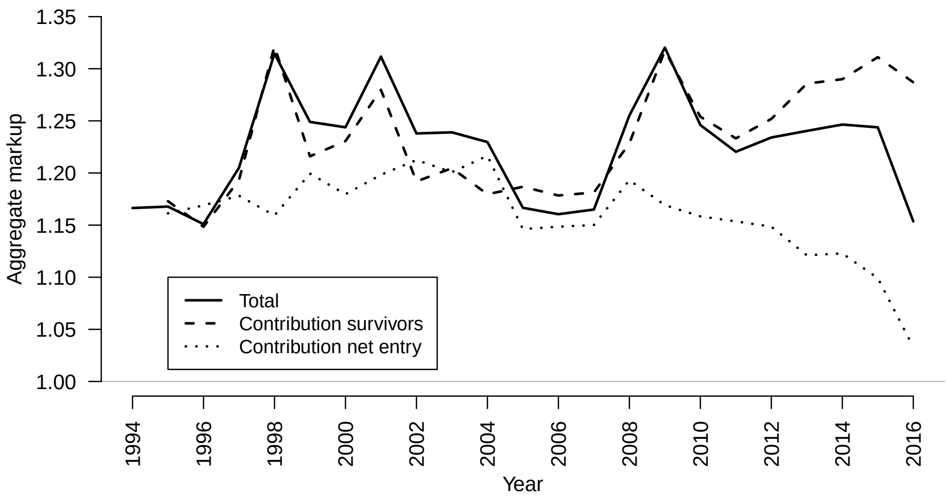

Figure 3.5: Aggregate markup decomposition with entry and exit

Figure 3.6 shows, in addition, the decomposition of the group of surviving firms into the within and between contribution. The within contribution (dotted-dashed line), i.e. surviving firms contribution to the aggregate markup through average markup variation, is minor at the beginning of the period but becomes dominant over time as it follows always closer the overall aggregate contribution of surviving firms (dashed line). The between contribution (long-dashed line), i.e. surviving firms' contribution to aggregate markup through reallocation in sales shares, plays an important role at the beginning of the period. This leads to relatively high volatility in surviving firms' markup variation until 2002, whereupon reallocation effects become minor.

[26]See Appendix 3.13.2, Table 3.9 for exact figures.

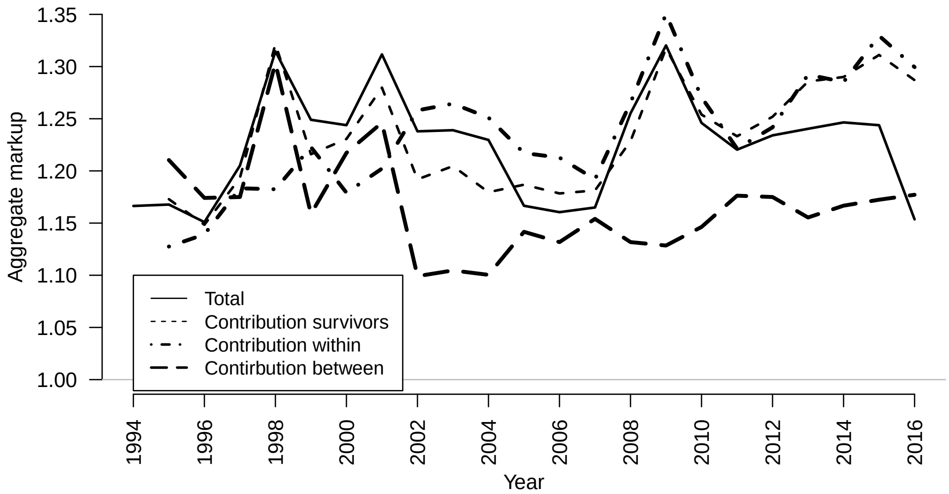

Figure 3.6: Aggregate markup decomposition with entry and exit

3.7 Heterogeneity in aggregate productivity and markup across sectors

To provide some insight into heterogeneity in the aggregate measures among sectors, I compute both aggregate productivity and markups across years, for each of the 2-digit sector separately. Figure 3.7 illustrates heterogeneity w.r.t. aggregate productivity and shows that there is substantial variation. Some sectors, such as the manufacturing for wearing apparel, reveal an aggregate log productivity of only 0.28, whereas others, such as the manufacturing of other transport equipment, reveals a high productivity, given by 1.20, which is a dramatic difference. Similarly, Figure 3.8 shows the aggregate markup across sectors. Most sectors are above an aggregate productivity of one, i.e., on average prices are higher compared to marginal costs. Sector 24 (basic metals) and 29 (motor vehicles etc.) show an aggregate markup of somewhat below one. More drastically, sector 30 (other transport equipment) shows an aggregate markup far below one. This is induced by a relatively low (high) estimated output elasticity (output share) w.r.t. materials and a higher share of measured markdowns (share of firms reporting a markup < 1), probably weighted by larger sales shares. Caselli et al. (2018) measure for the French manufacturing that about 14% of firms reveal markdowns. I find a somewhat smaller share of markdowns, given by about 10%.[27]

[27]See Appendix 3.12, Table 3.7, for estimated median elasticities for each sector as well as Appendix 3.15 Figure 3.19, illustrating markdowns per sector.

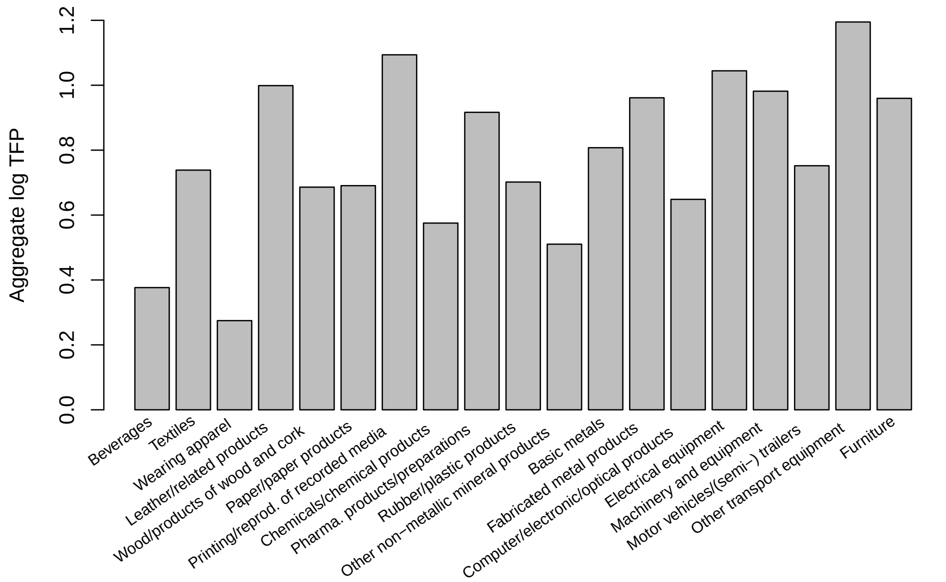

Figure 3.7: Heterogeneity in aggregate productivity among sectors

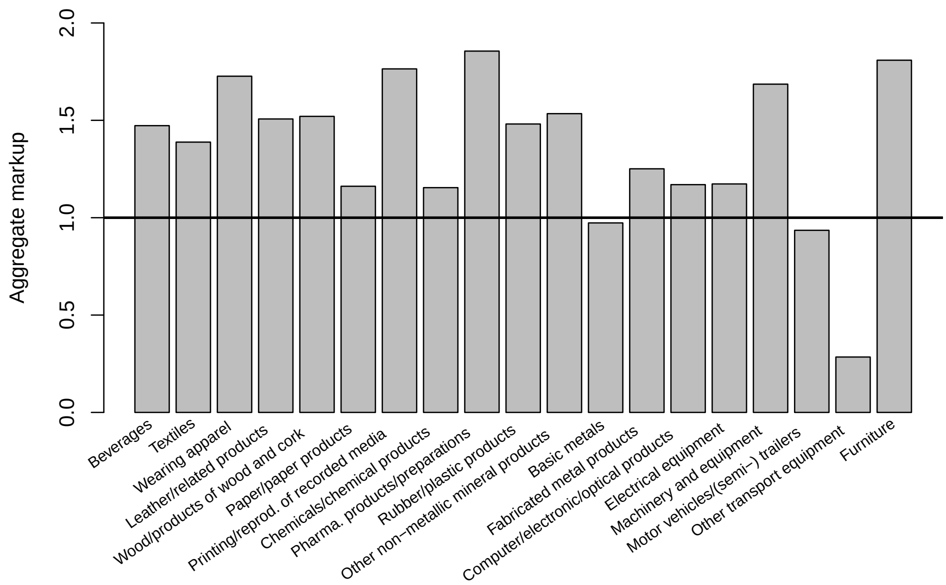

Figure 3.8: Heterogeneity in aggregate markup among sectors

3.8 Distribution and convergence patterns of productivity and markups

In this section I investigate the distribution of firm-level productivity and markup. I first investigate the evolution of different percentiles over time, whereupon I concentrate on convergence patterns of both distributions.

3.8.1 Distribution over time of productivity and markups

Figure 3.9 shows different percentiles overtime of the productivity distribution. The top line represents the highest percentile, here given by the 95*th* percentile of the productivity distribution. The lines below represent the 75*th*, 50*th*, 25*th*, and 5*th* percentile, respectively. The solid line represents, as benchmark, the weighted average. The figure shows that (log) productivity levels increase relatively synchronously over all reported percentiles of the distribution. It can also be seen, that the weighted average, i.e. the here presented aggregate productivity measure, increases relatively more compared to the different percentiles. Figure 3.10 shows the same percentiles of the markup distribution throughout the years as well as the weighted average. The evolution the 95*th* percentile of the markup distribution declines over 2002 and 2011, whereupon the level stabilizes. This pattern is actually very similar to the one observed w.r.t. the number of firms over time (Figure 3.2), where likewise from 2002 on the number of firms constantly decreases. This suggests that relatively high markup firms have left the industry. All other percentiles of the distribution are quite stable over time with a very similar pattern compared to the weighted average. This finding also contrasts De Loecker et al. (2020) finding for the US that the rise in aggregate markups between 1980 and 2016 is mainly driven by an increase in markups of few high markup firms.

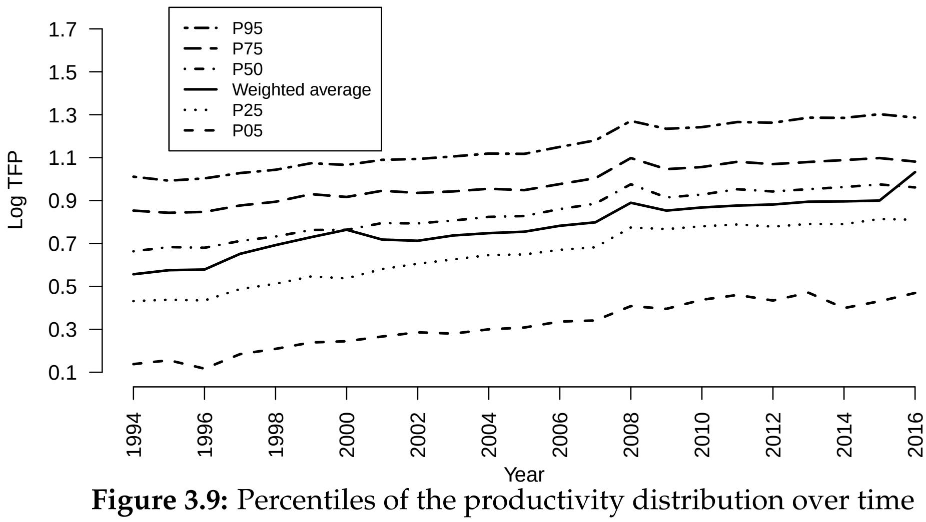

Figure 3.9: Percentiles of the productivity distribution over time

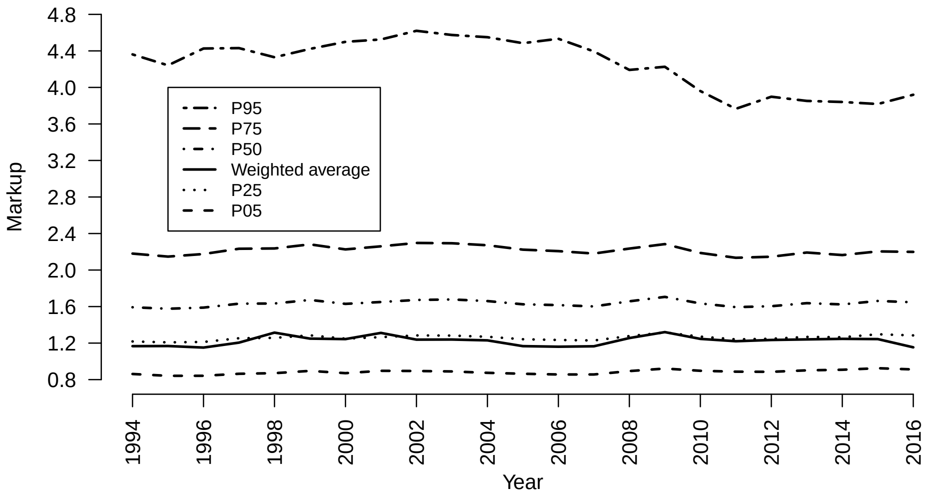

Figure 3.10: Percentiles of the markup distribution over time

3.8.2 Convergence patterns of productivity and markups

To investigate convergence pattern among firms w.r.t. productivity and markups I follow Cette et al. (2017). In the context of productivity convergence they suggest to define a frontier at the 95th percentile and to track over time the median productivity level of the bottom 95% and the top 5% of the productivity distribution. Figure 3.11 illustrates the evolution of the median related to the bottom 95th and the top 5% of the productivity distribution. Note that I here normalize the productivity w.r.t. the initial year 1994, meaning that both medians are equal to one at that year. Relative to the initial level at 1994, the median of the bottom 95% of the productivity distribution, given by the dashed line, increases faster compared the median productivity of the top 5%. Also the gap between both medians increases with time, which corresponds to a catch-up process between low- and high-productivity firms. A similar result is found by Cette et al. (2017). Figure 3.12 provides the analogous comparison for markups. The figure shows that both the median of the bottom 95% and the median of the top 5% of the markup distribution evolve relatively similarly until 2007, whereupon I measure a sharp decrease in the median of the top 5%. Instead, the median of the bottom 95% experiences a short increase but then stabilizes. According to my measures, the gap between the bottom 95% and the top 5% reduces considerably from 2007 on.

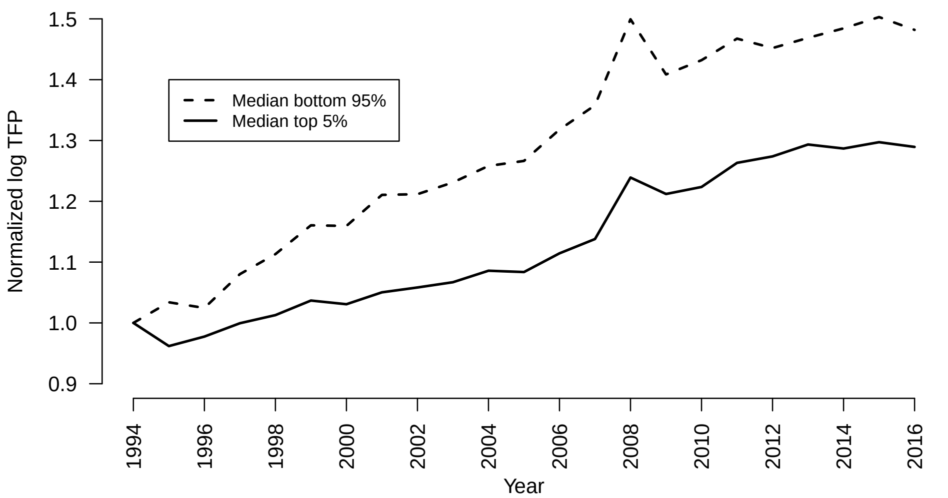

Figure 3.11: Productivity convergence among firms, bottom 95% vs. top 5%

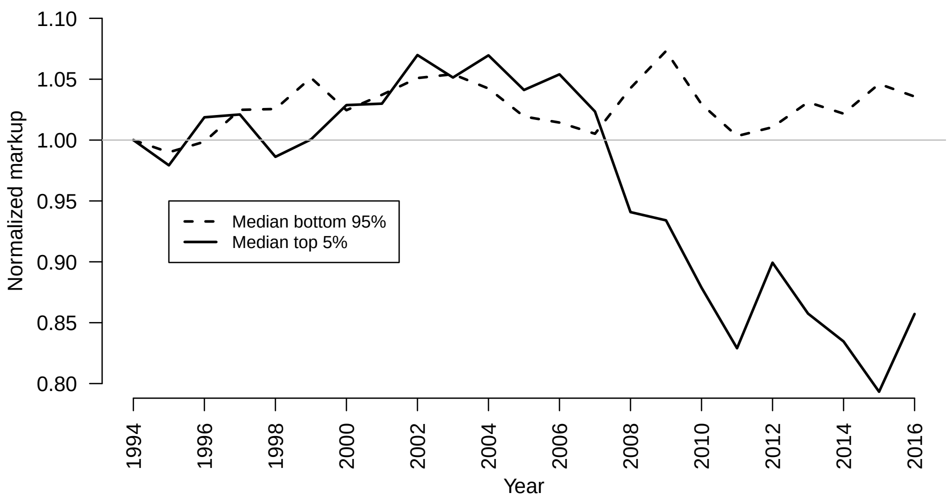

Figure 3.12: Markup convergence among firms, bottom 95% vs. top 5%

3.9 Relation between markups, productivity, firm entry and exit

The markup decomposition discussed above provides empirical evidence that entering (exiting) firms contribute negatively (positively) to the aggregate evolution, suggesting lower (higher) markups compared to the group of surviving firms. In this section, I further investigate in a regression framework the relation between markups and firm characteristics, such as firms' status in terms of market entry and exit, as well as productivity. Syverson

(2019) describes the relation between markups and productivity in the following: Remember that a firm's markup is given by $\mu_{nt} = P_{nt}/\lambda_{nt}$, with P_{nt} and λ_{nt} denoting the output price and marginal cost. Marginal cost, in turn, can be described as a function of input prices and productivity, where the marginal cost is positively (negatively) correlated with input prices (productivity). That is, if a firm's productivity rises, everything else hold equal, marginal costs should decrease and, as a result, markups should increase. It should be noted, however, as the productivity estimate, in my setting, is essentially a residual of a 'sales-generating production function', it also contains unobserved quality differences both in input and output, as well as market power effects. In other words, varying productivity among firms might be induced by quality differences in output/inputs and/or by varying market power of firms. When investigating the markup premium of entering/exiting firms it is therefore important to include productivity to control for these variations.

To study this relation, I follow De Loecker and Warzynski (2012) and run the following regression:

$$\log(\mu_{nt}) = \beta_0 + \beta_1 e^{+}_{nt} + \beta_2 e^{-}_{nt} + \beta_3 \omega_{nt} + \mathbf{b}'_{nt}\sigma + v_{nt}, \tag{3.20}$$

where the parameters of interest are given by β_1, β_2, and β_3, i.e., the average effect of firm entry, firm exit, and TFP on markups. Note that $e^{+}_{nt} = 1$ ($e^{-}_{nt} = 1$) if firm entry (exit) is observed.[28] $\mathbf{b}_{nt}$ contains a set of control variables such as (log) capital and labor to capture firm size effects as well as 4-digits sector and time dummies, with σ a vector containing the corresponding coefficients, and v_{nt} is an error term, supposed to be uncorrelated with the regressors. As emphasized by De Loecker and Warzynski (2012), the parameters β_1 and β_2 should not be causally interpreted but serve to empirically test whether entrants/exitors have on average different markups. The markup difference is then computed by $\mu_{E/X} = \beta_{1/2}\exp(\beta_0)$.

Table 3.3 shows the results. Two models are estimated: (1) including only time fixed effects (FE) and (2) including both time and 4-digit FE. The preferred model is given by (2) as it yields a considerably higher adjusted R^2. The regression result shows a negative (positive) relation between log markups and entry (exit). More precisely, it turns out that $\widehat{\mu}_E = -0.014$ and $\widehat{\mu}_X = 0.043$, meaning that on average entering (exiting) firms reveal 1.4% (4.3%) lower (higher) markups compared to surviving firms, statistically significant at the 1% level. This confirms what we already saw at the aggregate level (Section 3.6), where the group of entering (exiting) firms contribute negatively (positively) to the overall aggregate markup. The fact that entering firms reveal on average lower markups compared to surviving firms, even when controlling for productivity that absorbs some variation in markups, means that entering firms tend to have less market power and/or adopt an aggressive price policy to persist in the market. The positive relation between markups and productivity, here given

[28]See Appendix 3.11.2 for the formal description of the variables for firm entry and exit.

by an estimated coefficient of 0.506, statistically significant at the 1% level, is expected. This is because of the described markup-marginal cost/productivity relation as well as by the productivity measure which is revenue based reflecting some variation in the markup. The estimated coefficients associated with the variables log capital and log labor, given by -0.029 and -0.040, statistically significant at the 1% level, implies (on average) a negative relation between firms' markup and firm size. This is a surprising result as, generally, larger firms are expected to have higher fixed costs (but lower marginal costs), which are supposed to be covered by setting higher markups (Berry et al., 2019). Technology differences among firms in terms of fixed and variable costs and their relation with markups are investigated more in detail by De Monte and Koebel (2021) using the same data.

Table 3.3: Markups and firm characteristics

	Dependent variable: log $(\widehat{\mu}_{nt})$	
	(1)	(2)
Intercept	0.450^{***}	0.356^{***}
	(0.003)	(0.006)
Entry (0/1)	-0.033^{***}	-0.010^{***}
	(0.002)	(0.002)
Exit (0/1)	0.028^{***}	0.030^{***}
	(0.002)	(0.002)
log TFP	0.434^{***}	0.506^{***}
	(0.002)	(0.004)
log Capital	-0.023^{***}	-0.029^{***}
	(0.000)	(0.000)
log Labor	-0.057^{***}	-0.040^{***}
	(0.001)	(0.001)
Time FE	Yes	Yes
4-digit FE	No	Yes
Adj. R^2	0.160	0.363
Num. obs.	796,261	796,261

a) $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$
b) Robust standard errors are reported in parenthesis.
c) The regressions exclude outliers in the top and bottom 3rd percentile of the markup distribution.
d) 4-digit FE (fixed effects): The 19 considered 2-digit sectors comprise 184 4-digit sectors.

3.10 Conclusion

This chapter investigates aggregate productivity and markups of French manufacturing firms, taking firm entry and exit into account. For this purpose, I use firm-level data covering the period from 1994 to 2016. Firm-level productivity and markups are estimated based in a gross output translog production function relying on Ackerberg et al. (2015) and De Loecker (2011). Applying the decomposition method presented by Melitz and Polanec (2015), my results show that aggregate productivity in the French manufacturing industry increases significantly between 1994 and 2016. Incumbent firms account for the largest share of aggregate productivity growth, which in turn is mainly a result of firms' learning process and less of reallocation of production from low productivity firms to high productivity firms. My findings provide evidence of a catch-up process within the French manufacturing industry as low productivity firms improve their productivity faster compared to high productivity firms. The findings w.r.t. productivity dynamics go largely in line with other studies using French data (Cette et al., 2017; Ben Hassine, 2019). Contrary to similar previous studies for the US economy, I find aggregate markups to remain relatively stable over time. For most periods incumbent firms have a positive contribution to aggregate markups, whereas the net entry contribution has a varying sign. Here, especially new market entrants appear to have a negative impact on the aggregate markup, pulling it down. Also, I find that over time high markup firms reduce their markup considerably, whereas the markups of lower markup firms remain at a relatively constant level, indicating that the dispersion of markups narrows over time. Finally, investigating the relationship between markups and firm characteristics by means of a regression framework, I find that markups are negatively (positively) related with firm entry (exit). This implies that entrants have less market power and/or adopt an aggressive price policy in order to remain in the market.

There are, however, several limitations of the study. Most importantly, using a Hicks neutral gross output translog production function implies a homothetic shift of the technology over time, letting the relative marginal productivities unaffected by productivity. This means that heterogeneity in output elasticities, for instance, is only due to differences in firms input mix but not to time-varying parameters and/or further unobserved sources of heterogeneity. This is certainly a meaningful limitation given the long sample period. Novel nonparametric production function estimation methods, such as developed by Gandhi et al. (2020) and Demirer (2020), are promising to prevent from misspecification issues. Further, I rely on a revenue based production function that does not take into account price heterogeneity in output and input markets, leading to biased estimates if output/input prices are correlated with firms' optimal quantity choices. The development and use of firm-level price indicators, as presented by Morlacco (2017), could prevent form such a bias. The study leaves open questions w.r.t the investigation of welfare implications related to the evolution of productivity and markup, such as presented in De Loecker et al. (2018) and Edmond et al. (2018). Also, I find a negative relation between markups and firm size, which invites for more in-dept research that takes firm size explicitly into account. Technological differences among firms are studied in more detail by De Monte and Koebel (2021) using the same data set.

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3.11 Appendix A: Data

3.11.1 Descriptive statistics

Table 3.4 illustrates averages over the period 1994-2016 w.r.t. each manufacturing sector in the sample. The table shows that sector 25 (manufacturing for fabricated metal products) states the largest sector in terms of the number of firms, including on average 25.7% of all firms and 13.3% of total employment. Instead, in terms of sales, sector 29 (manufacturing for motor vehicles/semi-(trailers), states the larges sector, with an average share of total sales of about 14.5%. Entry and exit rates are relatively stable across sectors. Here, the sector with the highest degree of firm dynamics is given by sector 14 (wearing apparel) with an average entry and exit rate of 6.1% and 8.7%, respectively.

Table 3.4: Summary statistics w.r.t. the included sectors: averages from 1994-2016[a,b]

2-digit sector[c]	# of firms	Share of firms	Share of empl.	Share of sales	Entry rate	Exit rate	Age
11	625	1.76	1.75	3.52	4.26	2.81	43.47
13	1541	4.35	2.89	1.88	3.65	4.88	22.73
14	1760	4.96	3.19	1.71	6.18	8.73	17.50
15	523	1.47	1.38	0.70	4.24	5.90	21.50
16	2467	6.96	2.77	1.84	4.05	3.99	19.98
17	938	2.65	3.40	3.45	3.13	3.76	23.20
18	3274	9.23	3.46	2.02	3.78	4.91	20.23
20	1382	3.90	7.67	12.46	3.77	4.50	23.20
21	284	0.80	3.65	5.43	3.89	4.94	25.07
22	2640	7.45	8.55	6.22	3.48	3.63	20.11
23	2072	5.84	5.47	4.66	4.40	4.83	21.54
24	618	1.74	3.96	5.13	4.32	3.76	22.45
25	9142	25.78	13.30	8.67	4.27	3.45	20.42
26	1343	3.79	6.59	6.65	5.66	6.08	18.51
27	1139	3.21	6.06	5.13	4.55	4.70	21.25
28	2788	7.86	7.89	6.92	4.99	4.86	20.88
29	986	2.78	10.43	14.50	4.00	3.95	20.64
30	328	0.93	5.16	7.82	5.05	4.76	20.63
31	1609	4.54	2.45	1.31	4.28	5.05	18.08
Total	35459	100.00	100.00	100.00	4.29	4.48	20.94

[a] All figures represent averages over the whole period 1994-2016. Shares and rates are given in %.

[b] 11-beverages, 13-textiles, 14-wearing apparel, 15-leather/related products, 16-wood/products of wood and cork, 17-paper/paper products, 18-printing/reproduction of recorded media, 20-chemicals/chemical products, 21-pharmaceutical products/preparations, 22-rubber/plastic products, 23-other non-metallic mineral products, 24-basic metals, 25-fabricated metal products, 26-computer, electronic, and optical products, 27-electrical equipment, 28-machinery and equipment, 29-motor vehicles/(semi-) trailers, 30-other transport equipment, 31-furniture.

3.11.2 Measuring firm entry and exit at a yearly basis

I here define firms' status being survivor, entrant, or exitor, which might change from year to year. Let $a_{nt} \in \{0, 1\}$ be a firm state variable, taking the value 0 in case of inactivity, and 1, if the firm is active. A firm is said to be active at t, if it reports nonzero data for one of the following variables: total production, turnover and/or net profits. In all other cases the firm is supposed to be inactive. Further, survival is denoted by $s_{nt} \in \{0, 1\}$ with $s_{nt} = 1$ if $a_{n,t-1} = a_{nt} = a_{n,t+1} = 1$. Entry is denoted by $e^+_{nt} \in \{0, 1\}$ with $e^+_{nt} = 1$ if $a_{n,t-1} = 0$ and $a_{nt} = a_{n,t+1} = 1$. Exit is denoted by $e^-_{nt} \in \{0, 1\}$ with $e^-_{nt} = 1$ if $a_{n,t-1} = a_{nt} = 1$ and $a_{n,t+1} = 0$. In the literature, firm entry and exit is often measured by looking one period ahead (see for instance Blanchard et al. (2014)). It is then specified that $e^+_{nt} = 1$ if $a_{n,t-1} = 0$ and $a_{n,t} = 1$, and similarly with firm exit. However, measuring entry and exit in this way introduces some ambiguity with respect to the identification of entrants and exitors. This can be seen in Table 3.5. In the very last row, where the firm is only active at t, it could be considered as an entrant and/or exitor at t. Instead, I prefer to use the alternative convention and consider firms exhibiting an activity sequence as described in the last row of Table 3.5 as unidentified. Note that the sample contains only firms reporting at least five full-time employees. I control for the case if firms cross the threshold of five employees, to prevent from counting excess entry and exit.

Table 3.5: Firm status example

Variable activity (0/1)				
$a_{n,t-1}$	a_{nt}	$a_{n,t+1}$	Status at t	Binary firm status variables at t
1	1	1	Survivor	$s_{nt} = 1,\ e^+_{nt} = 0,\ e^-_{nt} = 0$
0	1	1	Entrant	$s_{nt} = 0,\ e^+_{nt} = 1,\ e^-_{nt} = 0$
1	1	0	Exitor	$s_{nt} = 0,\ e^+_{nt} = 0,\ e^-_{nt} = 1$
0	1	0	Not identified	$s_{nt} = 0,\ e^+_{nt} = 0,\ e^-_{nt} = 0;$

3.12 Appendix B: Translog production function estimation

I here present the results from the TL production function estimation, conducted for each 2-digit sector separately. In particular, Table 3.6 provides the coefficient estimates, which, however, are not easily interpretable. Table 3.7 shows, the more informative corresponding median output elasticity w.r.t. the inputs capital, labor, and materials, as well as the median returns to scale. Further, the corresponding median absolute deviation (MAD) as well as the share of negative estimates are reported. Figure 3.13 illustrates the kernel density estimates of output elasticities and returns to scale over all firms and years. It can be seen that the output elasticity w.r.t. capital input is strongly concentrated around 0.1. Instead, the density of the elasticity w.r.t. labor is highest around 0.4. The density of the elasticity w.r.t. materials shows a bi-modal pattern, with a higher concentration between 0.3 and 0.4, as well as between 0.5 and 0.6. Returns to scale are highly concentrated around 1.0 and 1.05, indicating that most firms have constant returns to scale. Additionally, Figure 3.14 illustrates the median output elasticities and returns to scale over time. It can be seen that even though the coefficients of the TL production function are supposed to be fixed over time, the production technology, in terms of the output elasticity for a given input, might change through changes in firms' input mix. The figure shows that the median output elasticity of labor is higher at the beginning of the period and decreases over time, while the median output elasticity w.r.t. materials slightly increases.

Also, the first stage of the production function estimation allows to recover the production function residual $\widehat{\epsilon}_{nt}$ (equation (3.6)). It is then further used to recover firm-level productivity (equation (3.14)) as well as to estimate the input share of materials to derive firm-level markups (equation (3.15) and (3.17)). Figure 3.15 shows the kernel density estimate of the residual, with a strong concentration around zero, close to normality.

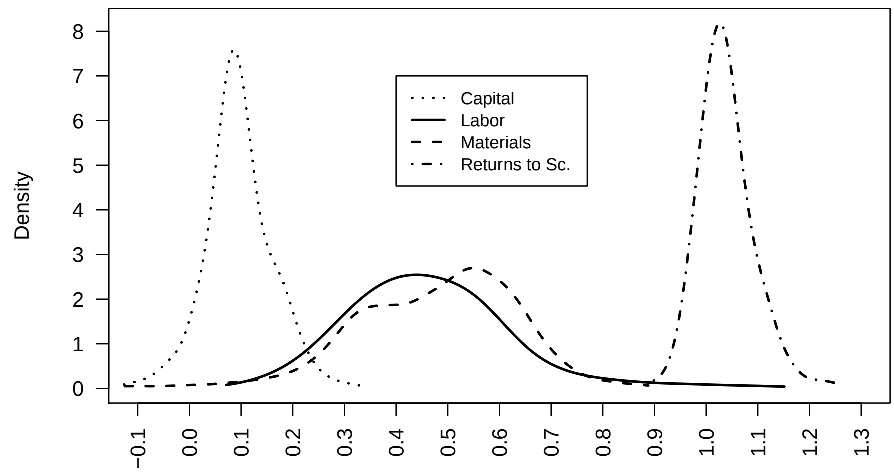

Figure 3.13: Kernel density estimates of output elasticities and returns to scale

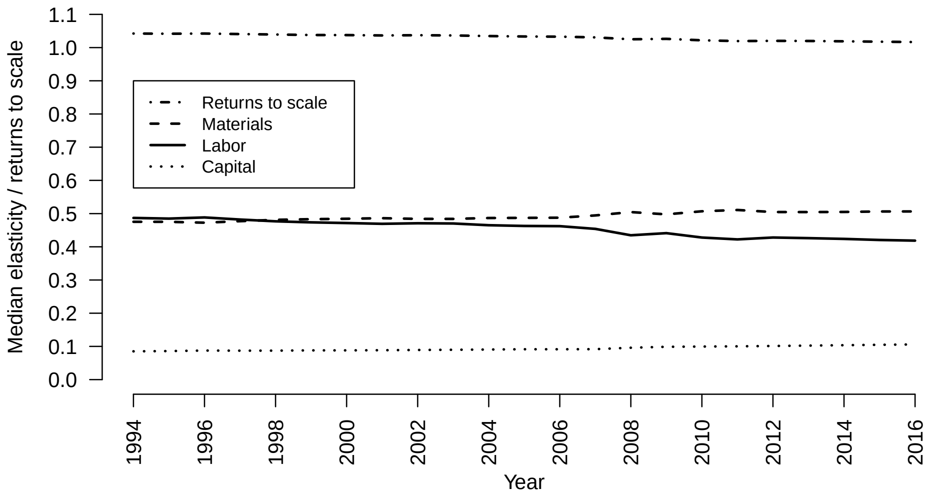

Figure 3.14: Median output elasticities and returns to scale over time

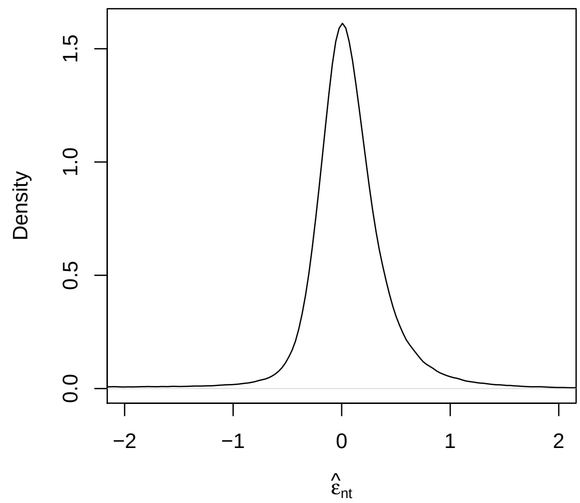

Figure 3.15: Distribution of residuals from the first stage of the production function estimation

Table 3.6: Coefficients estimates of the TL production function (ACF)

Sector	$\widehat{\alpha}_K$	$\widehat{\alpha}_L$	$\widehat{\alpha}_M$	$\widehat{\alpha}_{KK}$	$\widehat{\alpha}_{LL}$	$\widehat{\alpha}_{MM}$	$\widehat{\alpha}_{KL}$	$\widehat{\alpha}_{KM}$	$\widehat{\alpha}_{ML}$	# Obs.	# Firms
Beverages	0.060	0.368	0.661	0.080	-0.019	0.100	0.030	-0.087	-0.021	12743	1330
	(0.0026)	(0.0192)	(0.0328)	(0.0044)	(0.0000)	(0.0048)	(0.0010)	(0.0041)	(0.0010)		
Textiles	0.138	0.157	0.681	0.047	0.168	0.123	-0.023	-0.037	-0.110	31761	3599
	(0.0070)	(0.0076)	(0.0338)	(0.0024)	(0.0081)	(0.0062)	(0.0013)	(0.0014)	(0.0055)		
Wearing apparel	0.137	0.318	0.721	0.028	0.101	0.155	-0.013	-0.022	-0.124	33225	5384
	(0.0079)	(0.0142)	(0.0364)	(0.0013)	(0.0061)	(0.0078)	(0.0012)	(0.0010)	(0.0063)		
Leather/	0.123	0.100	0.759	0.028	0.189	0.120	-0.026	-0.011	-0.132	10553	1337
related products	(0.0065)	(0.0025)	(0.0395)	(7e-04)	(0.0109)	(0.0058)	(0.0016)	(0.0008)	(0.0077)		
Wood/products of	0.134	0.196	0.581	0.015	0.103	-0.034	-0.083	0.052	0.005	50589	5538
wood and cork	(0.0102)	(0.0107)	(0.0286)	(0.0028)	(0.0090)	(0.0024)	(0.0053)	(0.0017)	(0.0034)		
Paper/	0.078	0.238	0.659	0.059	0.126	0.097	-0.013	-0.040	-0.082	19862	1937
paper products	(0.0030)	(0.0095)	(0.0349)	(0.0031)	(0.0068)	(0.0050)	(7e-04)	(0.0016)	(0.0048)		
Printing/reprod.	0.163	0.006	0.735	0.001	0.257	0.074	-0.039	0.015	-0.143	66497	7911
of recorded media	(0.0078)	(0.0015)	(0.0362)	(6e-04)	(0.0126)	(0.0049)	(0.0024)	(9e-04)	(0.0074)		
Chemicals/	0.177	0.130	0.746	0.095	0.168	0.101	-0.035	-0.070	-0.076	28717	3043
chemical products	(0.0093)	(0.0056)	(0.0371)	(0.0046)	(0.0082)	(0.0049)	(0.0016)	(0.0035)	(0.0035)		
Pharma. products/	0.177	0.024	0.790	0.064	0.123	0.102	-0.017	-0.060	-0.065	5902	640
preparations	(0.0097)	(0.0012)	(0.0407)	(0.0034)	(0.0075)	(0.0051)	(0.0014)	(0.0030)	(0.0035)		
Rubber/	0.144	0.128	0.637	-0.010	0.141	0.048	-0.016	0.009	-0.069	55614	5494
plastic products	(0.0078)	(0.0075)	(0.0314)	(0.0012)	(0.0071)	(0.0039)	(0.0013)	(0.0000)	(0.0041)		
Other non-metallic	-0.011	0.561	0.594	0.048	0.008	0.085	0.017	-0.038	-0.063	42255	4792
mineral products	(0.0001)	(0.0275)	(0.0294)	(0.0014)	(0.0009)	(0.0042)	(7e-04)	(0.0013)	(0.0031)		
Basic metals	0.126	0.251	0.622	0.064	0.180	0.107	-0.037	-0.028	-0.109	12978	1354
	(0.0065)	(0.0104)	(0.0318)	(0.0029)	(0.0093)	(0.0052)	(0.0021)	(0.0001)	(0.0056)		
Fabricated metal	0.201	0.257	0.496	0.044	0.149	0.067	-0.034	-0.030	-0.065	191460	19405
products	(0.0100)	(0.0126)	(0.0246)	(0.0022)	(0.0076)	(0.0043)	(0.0023)	(0.0006)	(0.0039)		
Computer/electronic/	0.100	-0.024	0.790	-0.011	0.245	0.096	-0.003	0.013	-0.158	26831	3423
optical products	(0.0056)	(0.0006)	(0.0390)	(0.0013)	(0.0103)	(0.0057)	(0.0008)	(0.0001)	(0.0073)		
Electrical equipment	0.193	0.005	0.719	0.043	0.220	0.123	-0.032	-0.031	-0.124	23439	2602
	(0.0098)	(0.0020)	(0.0345)	(0.0022)	(0.0100)	(0.0061)	(0.0015)	(0.0017)	(0.0056)		
Machinery and	0.182	-0.093	0.778	-0.009	0.309	0.083	-0.058	0.031	-0.147	57187	6446
equipment	(0.0102)	(0.0050)	(0.0403)	(0.0026)	(0.0172)	(0.0054)	(0.0036)	(0.0001)	(0.0087)		
Motor vehicles/	0.246	0.083	0.654	0.070	0.214	0.117	-0.063	-0.033	-0.103	20532	2191
(semi-) trailers	(0.0105)	(0.0054)	(0.0336)	(0.0034)	(0.0101)	(0.0064)	(0.0023)	(0.0017)	(0.0058)		
Other transport	0.166	-0.094	0.832	0.080	0.323	0.110	-0.054	-0.031	-0.160	6656	806
equipment	(0.0090)	(0.0054)	(0.0399)	(0.0026)	(0.0164)	(0.0063)	(0.0021)	(0.0015)	(0.0083)		
Furniture	0.120	-0.021	0.800	0.014	0.192	0.101	-0.030	-0.008	-0.105	32234	4007
	(0.0060)	(0.0015)	(0.0416)	(0.0012)	(0.0108)	(0.0047)	(0.0016)	(0.0003)	(0.0068)		

Note: Standard errors are bootstrapped using 400 replications and reported in parenthesis.

Table 3.7: Translog production function: Median output elasticities w.r.t. inputs and return to scales

Sector	Statistic	Capital	Labor	Materials	Return to Scales
All	Elasticity	0.122	0.461	0.474	1.045
	MAD	0.039	0.097	0.113	0.031
	Share<=0	3.160	0.190	1.160	0.000
Beverages	Elasticity	0.159	0.361	0.606	1.124
	MAD	0.059	0.020	0.065	0.013
	Share<=0	5.010	0.000	0.330	0.000
Textiles	Elasticity	0.124	0.435	0.455	1.011
	MAD	0.038	0.109	0.092	0.053
	Share<=0	2.490	0.620	1.000	0.000
Wearing apparel	Elasticity	0.104	0.471	0.528	1.104
	MAD	0.046	0.202	0.253	0.024
	Share<=0	0.910	0.140	14.230	0.000
Leather/	Elasticity	0.083	0.441	0.521	1.039
related products	MAD	0.013	0.097	0.070	0.031
	Share<=0	0.330	0.410	1.180	0.000
Wood/products of	Elasticity	0.101	0.390	0.555	1.044
wood and cork	MAD	0.031	0.068	0.036	0.015
	Share<=0	5.810	0.030	0.000	0.000
Paper/	Elasticity	0.097	0.404	0.532	1.032
paper products	MAD	0.037	0.048	0.050	0.016
	Share<=0	5.760	0.000	0.230	0.000
Printing/reprod.	Elasticity	0.130	0.480	0.431	1.042
of recorded media	MAD	0.008	0.084	0.049	0.038
	Share<=0	0.000	0.130	0.150	0.000
Chemicals/	Elasticity	0.130	0.371	0.594	1.087
chemical products	MAD	0.063	0.074	0.081	0.033
	Share<=0	8.790	0.620	0.590	0.000
Pharma. products/	Elasticity	0.148	0.265	0.626	1.034
preparations	MAD	0.052	0.058	0.082	0.019
	Share<=0	7.110	1.190	0.260	0.000
Rubber/	Elasticity	0.111	0.395	0.551	1.050
plastic products	MAD	0.012	0.064	0.043	0.022
	Share<=0	0.000	0.020	0.020	0.000
Other non-metallic	Elasticity	0.100	0.464	0.496	1.070
mineral products	MAD	0.034	0.059	0.054	0.026
	Share<=0	0.630	0.000	0.090	0.000
Basic metals	Elasticity	0.113	0.484	0.448	1.039
	MAD	0.037	0.089	0.068	0.022
	Share<=0	4.970	0.330	0.340	0.000
Fabricated metal	Elasticity	0.178	0.545	0.312	1.035
products	MAD	0.029	0.054	0.046	0.027
	Share<=0	0.070	0.000	0.200	0.000
Computer/electronic/	Elasticity	0.119	0.446	0.481	1.048
optical products	MAD	0.026	0.131	0.079	0.045
	Share<=0	2.510	0.880	2.350	0.000
Electrical equipment	Elasticity	0.095	0.389	0.541	1.023
	MAD	0.031	0.089	0.078	0.026
	Share<=0	2.480	0.370	1.600	0.000
Machinery and	Elasticity	0.048	0.454	0.554	1.046
equipment	MAD	0.029	0.121	0.065	0.049
	Share<=0	17.660	0.400	0.610	0.000
Motor vehicles/	Elasticity	0.101	0.392	0.558	1.045
(semi-) trailers	MAD	0.046	0.077	0.064	0.020
	Share<=0	6.820	0.340	1.420	0.000
Other transport	Elasticity	0.107	0.580	0.429	1.103
equipment	MAD	0.041	0.168	0.126	0.069
	Share<=0	5.850	0.950	5.330	0.000
Furniture	Elasticity	0.085	0.339	0.611	1.029
	MAD	0.012	0.067	0.049	0.020
	Share<=0	0.240	0.100	0.060	0.000

Note: MAD denotes the Median Average Deviation.

3.13 Appendix C: Decomposition analysis

3.13.1 Derivation of the DOPD approach

In the framework of the DOPD approach, aggregate productivity/markup is decomposed in the following way: Let $S_{Gt} = \sum_{n \in G} s_{nt}$ denote the aggregate sales share of a group G, where $G = (E, S, X)$ indexes the group of entrants, survivors, and exitors. A group's aggregate productivity is then defined by $\Phi_{Gt} = \sum_{n \in G} (s_{nt}/S_{Gt})\, \phi_{nt}$, where ϕ_{nt} denotes the firm-level measure of either TFP or markup. Consider two periods, $t-k$ and t, where firms from $t-k$ to t either survive or exit the market. That is, the set of active firms at $t-k$ is composed of those firms that will survive and those that will finally exit the market at some period s with $t-k \leq s < t$. At t the set of active firms is composed of those firms that have survived from $t-k$ and new firms that have entered the market at some period s with $t-k < s \leq t$. According to the DOPD approach presented by Melitz and Polanec (2015), the aggregate measure at $t-k$ and t is described by

$$\begin{aligned} \Phi_{t-k} &= S_{S,t-k}\Phi_{S,t-k} + S_{X,t-k}\Phi_{X,t-k} = \Phi_{S,t-k} + S_{X,t-k}(\Phi_{X,t-k} - \Phi_{S,t-k}) \\ \Phi_{t} &= S_{S,t}\Phi_{S,t} + S_{E,t}\Phi_{E,t} = \Phi_{S,t} + S_{E,t}(\Phi_{E,t} - \Phi_{S,t}). \end{aligned}$$

Adding to the first equality of the first and second line $S_{X,t-k}\Phi_{S,t-k} - S_{X,t-k}\Phi_{S,t-k}$ and $S_{E,t}\Phi_{S,t} - S_{E,t}\Phi_{S,t}$, respectively, and recognizing that $S_{S,t-k} + S_{X,t-k} = 1$ and $S_{S,t} + S_{E,t} = 1$ yields the second equality.

Hence, the aggregate's growth between $t-k$ and t can be expressed by

$$\Phi_t - \Phi_{t-k} = \underbrace{\Phi_{S,t} - \Phi_{S,t-k}}_{\text{Contr. survivors}} + \underbrace{S_{E,t}(\Phi_{E,t} - \Phi_{S,t}) + S_{X,t-k}(\Phi_{S,t-k} - \Phi_{X,t-k})}_{\text{Contr. Net-entry}}.$$

As shown in the main text, the contribution of survivors can be further decomposed into its within and between contribution.

3.13.2 Decomposition tables for both aggregate productivity and markups

Table 3.8 and 3.9 present the aggregate measures, graphically shown in the main text. That is, the tables contain of aggregate productivity/markup (and aggregate sales shares) of the group of survivors, entrants, and exitors as well as these groups' contribution to the aggregate. Note that the index t corresponds to the respective year (column 1), whereas the index $t-k$ always corresponds to the measure at the initial year 1994. This means that contributions to the aggregate measure are always cumulatively w.r.t. 1994.

Table 3.8: DOPD: Aggregate productivity 1994-2016

Year (t)	Φ_t	$\Phi_{S,t}$	$S_{S,t}$	$\Phi_{S,t-k}$	$S_{S,t-k}$	Contr. Surv.	Contr. Within	Contr. Between	$\Phi_{E,t}$	$S_{E,t}$	Contr. Entry.	$\Phi_{X,t-k}$	$S_{X,t-k}$	Contr. Exit.	Contr. Net-E
1994	0.557	0.556	96.28	-	-	-	-	-	-	-	-	-	-	-	-
1995	0.576	0.578	94.91	0.556	96.28	0.021	-0.000	0.021	0.536	5.09	-0.002	0.559	3.72	-0.000	-0.002
1996	0.579	0.579	91.61	0.557	93.33	0.021	-0.004	0.025	0.579	8.39	0.000	0.545	6.67	0.001	0.001
1997	0.652	0.654	86.87	0.562	88.22	0.092	0.032	0.060	0.635	13.13	-0.002	0.515	11.78	0.006	0.003
1998	0.692	0.699	85.24	0.564	85.94	0.135	0.053	0.083	0.654	14.76	-0.007	0.513	14.06	0.007	0.001
1999	0.729	0.742	80.30	0.567	76.90	0.174	0.083	0.092	0.678	19.70	-0.013	0.520	23.10	0.011	-0.002
2000	0.764	0.785	75.78	0.559	71.78	0.226	0.076	0.150	0.699	24.22	-0.021	0.551	28.22	0.002	-0.019
2001	0.718	0.725	72.94	0.522	65.46	0.203	0.100	0.103	0.700	27.06	-0.007	0.622	34.54	-0.034	-0.041
2002	0.713	0.709	67.59	0.537	65.52	0.172	0.106	0.066	0.720	32.41	0.003	0.594	34.48	-0.020	-0.016
2003	0.737	0.736	65.27	0.534	61.51	0.202	0.117	0.085	0.740	34.73	0.002	0.593	38.49	-0.023	-0.021
2004	0.748	0.740	63.17	0.554	57.79	0.186	0.133	0.053	0.762	36.83	0.008	0.560	42.21	-0.003	0.006
2005	0.755	0.736	50.45	0.539	50.13	0.197	0.130	0.067	0.773	49.55	0.018	0.574	49.87	-0.017	0.001
2006	0.782	0.767	49.53	0.548	47.86	0.218	0.155	0.063	0.797	50.47	0.015	0.564	52.14	-0.008	0.007
2007	0.798	0.782	49.24	0.547	46.12	0.235	0.174	0.061	0.814	50.76	0.017	0.565	53.88	-0.010	0.007
2008	0.890	0.869	51.80	0.550	44.34	0.319	0.264	0.055	0.912	48.20	0.021	0.562	55.66	-0.007	0.014
2009	0.853	0.852	50.25	0.540	40.90	0.312	0.232	0.080	0.854	49.75	0.001	0.568	59.10	-0.016	-0.015
2010	0.868	0.856	48.59	0.533	39.22	0.323	0.249	0.074	0.879	51.41	0.012	0.572	60.78	-0.024	-0.011
2011	0.877	0.878	46.55	0.533	36.78	0.345	0.270	0.074	0.875	53.45	-0.001	0.570	63.22	-0.023	-0.025
2012	0.882	0.865	48.55	0.535	37.26	0.330	0.259	0.072	0.897	51.45	0.016	0.569	62.74	-0.022	-0.005
2013	0.895	0.875	42.86	0.538	36.02	0.337	0.276	0.061	0.909	57.14	0.020	0.567	63.98	-0.019	0.001
2014	0.896	0.884	42.61	0.540	35.13	0.344	0.274	0.070	0.905	57.39	0.013	0.566	64.87	-0.016	-0.004
2015	0.900	0.895	41.24	0.537	34.20	0.358	0.294	0.064	0.904	58.76	0.005	0.567	65.80	-0.020	-0.015
2016	1.033	0.880	37.20	0.538	32.95	0.341	0.283	0.058	1.123	62.80	0.153	0.566	67.05	-0.018	0.135

a) t refers to the respective year, while $t-k$ always refers to the initial year 1994. Contributions of survivors and net entry are, hence, always w.r.t. 1994.

b) Φ_G and S_G with $G = \{S, E, X\}$ denotes aggregate productivity and sales share of the group of survivors, entrants, and exitors. S_G are given in percent.

Table 3.9: DOPD: Aggregate markup 1994-2016

Year (t)	Φ_t	$\Phi_{S,t}$	$S_{S,t}$	$\Phi_{S,t-k}$	$S_{S,t-k}$	Contr. Surv.	Contr. Within	Contr. Between	$\Phi_{E,t}$	$S_{E,t}$	Contr. Entry.	$\Phi_{X,t-k}$	$S_{X,t-k}$	Contr. Exit.	Contr. Net-E
1994	1.166	1.155	96.28	-	-	-	-	-	-	-	-	-	-	-	-
1995	1.168	1.161	94.91	1.155	96.28	0.006	-0.039	0.044	1.292	5.09	0.007	1.472	3.72	-0.012	-0.005
1996	1.151	1.136	91.61	1.154	93.33	-0.018	-0.027	0.008	1.313	8.39	0.015	1.338	6.67	-0.012	0.003
1997	1.205	1.179	86.87	1.152	88.22	0.027	0.017	0.009	1.377	13.13	0.026	1.272	11.78	-0.014	0.012
1998	1.315	1.302	85.24	1.147	85.94	0.155	0.016	0.137	1.388	14.76	0.013	1.288	14.06	-0.020	-0.007
1999	1.249	1.230	80.30	1.180	76.90	0.050	0.056	-0.008	1.328	19.70	0.019	1.121	23.10	0.014	0.033
2000	1.244	1.246	75.78	1.182	71.78	0.064	0.013	0.051	1.238	24.22	-0.002	1.128	28.22	0.015	0.013
2001	1.312	1.324	72.94	1.210	65.46	0.113	0.036	0.080	1.280	27.06	-0.012	1.083	34.54	0.044	0.032
2002	1.238	1.225	67.59	1.200	65.52	0.026	0.092	-0.067	1.264	32.41	0.013	1.103	34.48	0.033	0.046
2003	1.239	1.234	65.27	1.196	61.51	0.038	0.098	-0.062	1.248	34.73	0.005	1.119	38.49	0.030	0.034
2004	1.230	1.219	63.17	1.206	57.79	0.013	0.085	-0.066	1.248	36.83	0.011	1.113	42.21	0.039	0.050
2005	1.167	1.266	50.45	1.246	50.13	0.020	0.051	-0.025	1.066	49.55	-0.099	1.087	49.87	0.079	-0.020
2006	1.160	1.260	49.53	1.248	47.86	0.012	0.046	-0.035	1.063	50.47	-0.099	1.092	52.14	0.081	-0.018
2007	1.165	1.262	49.24	1.247	46.12	0.015	0.026	-0.012	1.071	50.76	-0.097	1.097	53.88	0.081	-0.016
2008	1.255	1.309	51.80	1.247	44.34	0.062	0.099	-0.035	1.197	48.20	-0.054	1.102	55.66	0.081	0.027
2009	1.320	1.396	50.25	1.245	40.90	0.151	0.184	-0.038	1.244	49.75	-0.075	1.112	59.10	0.078	0.003
2010	1.246	1.327	48.59	1.239	39.22	0.088	0.104	-0.020	1.170	51.41	-0.081	1.119	60.78	0.073	-0.008
2011	1.220	1.292	46.55	1.226	36.78	0.067	0.055	0.010	1.158	53.45	-0.072	1.132	63.22	0.059	-0.013
2012	1.234	1.300	48.55	1.214	37.26	0.086	0.075	0.009	1.172	51.45	-0.066	1.138	62.74	0.048	-0.018
2013	1.240	1.340	42.86	1.221	36.02	0.119	0.126	-0.011	1.166	57.14	-0.100	1.136	63.98	0.054	-0.045
2014	1.246	1.339	42.61	1.216	35.13	0.124	0.119	0.000	1.178	57.39	-0.093	1.140	64.87	0.049	-0.044
2015	1.244	1.363	41.24	1.218	34.20	0.145	0.163	0.006	1.160	58.76	-0.119	1.139	65.80	0.052	-0.067
2016	1.154	1.343	37.20	1.222	32.95	0.121	0.133	0.011	1.041	62.80	-0.189	1.139	67.05	0.056	-0.133

[a] t refers to the respective year, while $t-k$ always refers to the initial year 1994. Contributions of survivors and net entry are, hence, always w.r.t. 1994.

[b] Φ_G and S_G with $G = \{S, E, X\}$ denotes aggregate markup and sales share of the group of survivors, entrants, and exitors. S_G are given in percent.

3.14 Appendix D: Robustness checks

3.14.1 Production function specification

As both firm-level productivity and markups are derived from the production function, empirical results presented in this study strongly depend the outcome of the estimation of the TL production function coefficients. The most natural way to check the results on robustness is to compare patterns of aggregate productivity and markups based on different production function specifications. For this purpose, I estimate a Cobb-Douglas (CD) gross output production function, given by

$$y_{nt} = \alpha_K x^k_{nt} + \alpha_L x^l_{nt} + \alpha_M x^m_{nt} + \omega_{nt} + \epsilon_{nt},$$

where α_K, α_L, and α_M denote technology parameters related to the output elasticities w.r.t. capital, labor and materials. The estimation routine is analogue to the one presented for the TL production function (Section 3.4). In particular, the first stage of the estimation of the CD production function is the same as for the TL production function. Only the second stage changes. The first stage yields $\widehat{f}(\cdot)$, here likewise approximated by a forth order polynomial in the inputs, based on which, in the case of a CD production function, we obtain

$$\widehat{\omega}_{nt}(\alpha) = \widehat{f}(x^k_{nt}, x^l_{nt}, x^m_{nt}, c_{nt}) - \alpha_K x^k_{nt} - \alpha_L x^l_{nt} - \alpha_M x^m_{nt},$$

with α = $\{\alpha_K, \alpha_L, \alpha_M\}$. The innovations in ω_{nt}, i.e., $\widehat{\xi}_{nt}$, can then be estimated by regressing $\widehat{\omega_{nt}}(\alpha)$ on a higher order polynomial of $\widehat{\omega_{n,t-1}}(\alpha)$ along with the exit dummy for some initial values for the parameters in α. For the second stage estimation I here use the following moment conditions to finally estimate the parameters of the CD specification:

$$E\left[\widehat{\xi}_{nt}(\alpha)\begin{pmatrix} x^k_{nt} \\ x^l_{nt} \\ x^m_{n,t-1} \end{pmatrix}\right] = 0$$

Table 3.10 presents the estimated coefficients as well as the resulting returns to scale, for each 2-digit sector. Using CD production function specification, for a given manufacturing sector, output elasticities no longer vary across firms, nor across time.

Table 3.10: Coefficient estimates of the Cobb-Douglas production function

Sector	$\widehat{\alpha}_K$	$\widehat{\alpha}_L$	$\widehat{\alpha}_M$	Returns to scale
Beverages	0.188	0.408	0.533	1.129
	(0.006)	(0.006)	(0.006)	
Textiles	0.102	0.474	0.418	0.994
	(0.003)	(0.004)	(0.002)	
Wearing apparel	0.097	0.550	0.378	1.025
	(0.004)	(0.004)	(0.002)	
Leather/related products	0.139	0.578	0.337	1.054
	(0.005)	(0.007)	(0.005)	
Wood/products of wood and cork	0.078	0.464	0.499	1.041
	(0.003)	(0.004)	(0.004)	
Paper/paper products	0.126	0.452	0.479	1.057
	(0.004)	(0.006)	(0.006)	
Printing/reprod. of recorded media	0.064	0.581	0.368	1.013
	(0.003)	(0.004)	(0.003)	
Chemicals/ chemical products	0.203	0.396	0.488	1.087
	(0.004)	(0.005)	(0.004)	
Pharma. products/ preparations	0.138	0.374	0.545	1.057
	(0.009)	(0.016)	(0.011)	
Rubber/plastic products	0.139	0.431	0.491	1.061
	(0.005)	(0.005)	(0.006)	
Other non-metallic mineral products	0.139	0.492	0.474	1.105
	(0.004)	(0.004)	(0.005)	
Basic metals	0.126	0.392	0.492	1.010
	(0.005)	(0.006)	(0.005)	
Fabricated metal products	0.124	0.553	0.319	0.996
	(0.000)	(0.002)	(0.001)	
Computer/electronic/optical products	0.135	0.581	0.408	1.124
	(0.009)	(0.010)	(0.009)	
Electrical equipment	0.108	0.497	0.414	1.019
	(0.003)	(0.005)	(0.004)	
Machinery and equipment	0.074	0.623	0.364	1.061
	(0.003)	(0.004)	(0.003)	
Motor vehicles/(semi-) trailers	0.140	0.516	0.408	1.064
	(0.005)	(0.006)	(0.005)	
Other transport equipment	0.125	0.684	0.313	1.122
	(0.016)	(0.011)	(0.008)	
Furniture	0.070	0.421	0.524	1.015
	(0.003)	(0.005)	(0.005)	

Note: Standard errors are bootstrapped using 400 replications and reported in parenthesis.

3.14.2 Aggregate productivity

Figure 3.16 compares aggregate (log) TFP derived from the TL production function (solid line) vs. aggregate (log) TFP derived from the CD specification (dashed line). Aggregate productivity based on the CD specification generally yields a lower aggregate log productivity level, but follows qualitatively a similar pattern compared to the outcome based on the TL specification. I therefore conclude that the results presented in the paper concerning the productivity growth patterns seem to be robust w.r.t. the specification of a TL production function.

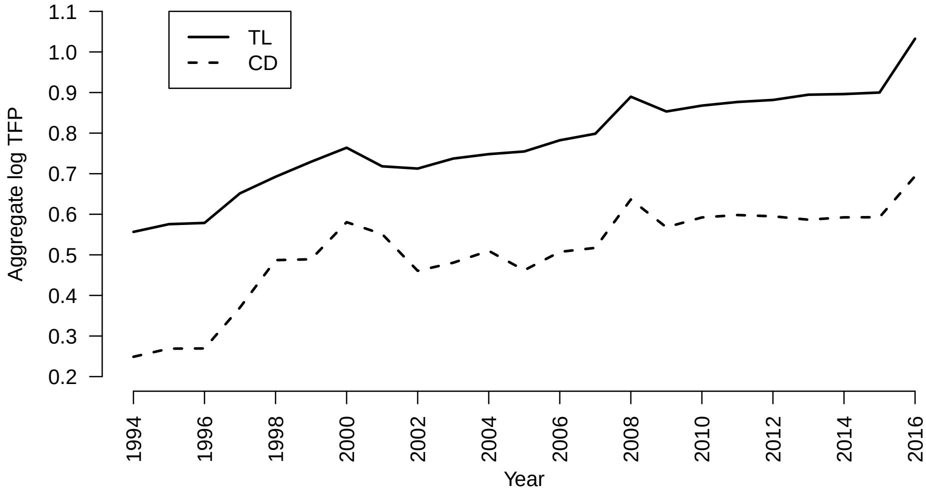

Figure 3.16: Aggregate log productivity: Translog (TL) vs. Cobb-Douglas (CD) production function

3.14.3 Aggregate markups

Remember first that aggregate markups are calculated as a weighted average of firm-level markup, given by

$$\widehat{\mu}_t = \sum_n \widehat{\mu}_{nt} s_{nt} \quad \text{with } \widehat{\mu}_{nt} = \frac{\widehat{\theta}^M_{nt}}{\widehat{\alpha}^M_{nt}},$$

where the first equality describes the weighted average of firms' markup weighted by their sales share. The markup is obtained by the ratio of the output elasticity and the input share w.r.t. materials, denoted by $\widehat{\theta}^M_{nt}$ and $\widehat{\alpha}^M_{nt}$. The aggregate markup changes for three reasons: (i) changing sales shares, (ii) changing output elasticities, and (iii) changing input shares.

Aggregate markups and changing output elasticity w.r.t. materials

To check for robustness of the aggregate markup measure I first compare the aggregate markups using the output elasticity w.r.t. materials $\widehat{\theta}^M_{nt}$, obtained from the TL production function, with aggregate markup when using the output elasticity from the CD production function. That is, in the latter case, $\widehat{\theta}^M_{nt} = \widehat{\alpha}_M$ implying constant elasticity across firms and years for a given 2-digit sector.

Figure 3.17 shows the results. While the aggregate markup seems to remain relatively constant over time when using the flexible firm-level output elasticity from the estimation of the TL production function, represented by the solid line, using a constant elasticity from the CD production function yields a considerable higher and increasing level of aggregate markup over time. Demirer (2020) in fact shows that a CD specification leads to under estimation of the output elasticity w.r.t. the fixed input and overestimation of the output elasticity of the flexible input, which consequently leads to an over estimation of markups. He argues that even when using a CES labor-augmented production function, this bias is only partially corrected, suggesting the need for a more flexible production function specification. To check the aggregate markup on its sensitivity w.r.t. the output elasticity, De Loecker et al. (2020) fix the output elasticity (in their case w.r.t. labor) to 0.85 and find much less sensitivity of the aggregate markup compared my experiment. However, their (time-varying) Cobb-Douglas specification is already relatively close to the counterfactual experiment when fixing the output elasticity to 0.85, which therefore might result in less differences in the aggregate measures compared to my case.

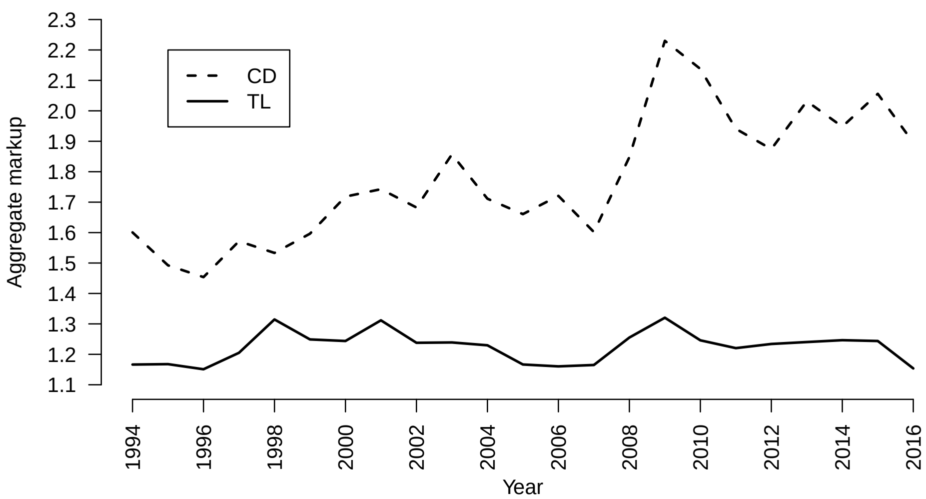

Figure 3.17: Aggregate markups: Using output elasticity based on translog (TL) vs. Cobb-Douglas (CD) production function

Aggregate markups and changing shares

The second robustness check w.r.t. the markup measure is done by replacing sales shares by total cost shares. A firm's total cost is defined by

$$C_{nt}^{tot} = P_t^k K_{nt} + P_t^l L_{nt} + P_t^m M_{nt},$$

where P_t denotes the user cost of capital, and P_t^l and P_t^m denote the labor and material price. In order to calculate the user cost of capital, I follow Hall and Jorgenson (1967), i.e., $P_t^k = P_t^I(1 + r_t) - P_{t+1}^I(1 - \delta_t)$, with P_t^I denoting the price index for investment, available at the 2-digit level, r_t is the long-run rate of interest, and δ_t the annual rate of capital depreciation, available at the sector level.[29] Labor price is firm specific and obtained by dividing the labor costs by the number of employees. Materials prices are only available at the sector level. A firm's total cost share is then given by $s_{nt}^C = C_{nt}^{tot} / \sum_n C_{nt}^{tot}$. Figure 3.18 illustrates the comparison. It can be seen that aggregate productivity based on firms' cost shares, given by the dashed line, yields an only slightly higher aggregate markup compared to the use of sales shares. The overall patterns of both curves, however, are very similar.

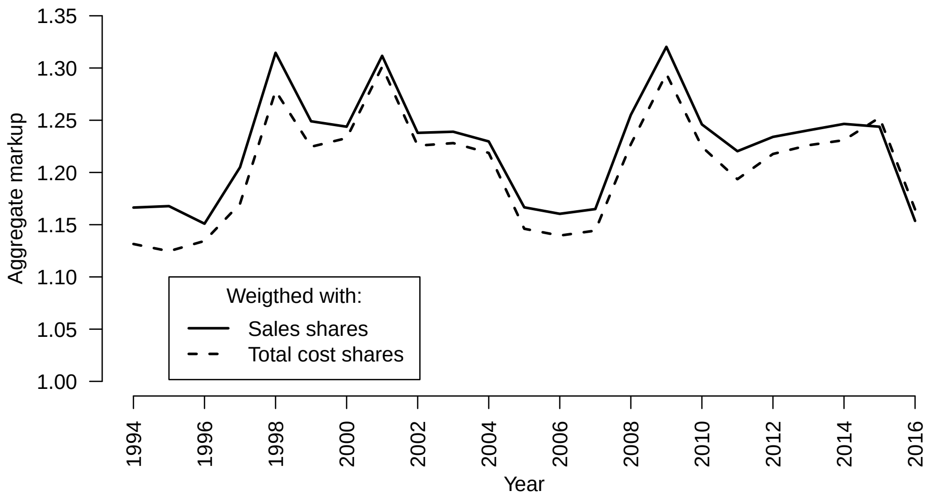

Figure 3.18: Aggregate markups: using sales shares vs. total cost shares

3.15 Appendix E: Further material

Figure 3.19 illustrates the share of markdowns for each sector. That is, each bar corresponds to the share of firms that reveal prices below the marginal costs, i.e. $\widehat{\mu}_{nt} < 1$. The sector for beverages exhibits the highest share of markdowns, given by more than 30 %. Other sectors, such as the sector for pharmaceutical products and the manufacture of furniture, only show a share of markdowns slightly larger than zero. These industries also show the highest aggregate markups (see Figure 3.8).

[29]The interest rate is provided by the Banque de France available at https://www.banque-france.fr/statistiques/taux-et-cours/taux-indicatifs-des-bons-du-tresor-et-oat, (April, 2021). δ_t is computed by the ratio of the consumption of fixed capital and fixed capital, available at www.insee.fr/fr/statistiques/2383652?sommaire=2383694, (April, 2021).

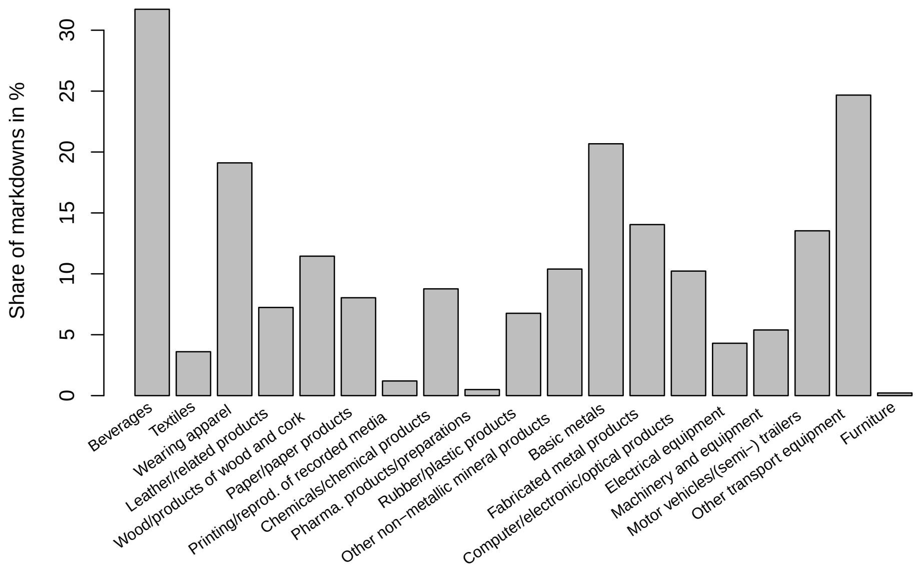

Figure 3.19: Share of markdowns (share of firms with markup<1) by sector

Table 3.11 provides some descriptive statistics for the estimated output shares w.r.t. capital, labor, and materials, given in the first column by $\widehat{a}^K_{nt}$, $\widehat{a}^L_{nt}$, and $\widehat{a}^M_{nt}$. All shares are estimated analogously to the output share w.r.t. materials, presented in the main text in equation (3.17). The table shows that among all inputs, the output share w.r.t. capital is the smallest, given with a mean of 7.71%. Here, firms at the $10th$ ($90th$) percentile exhibit an output share w.r.t. capital of 1.42% (15.47%). The highest output share is given for labor, with a median of 46.55%, which is somewhat higher compared to the median output share w.r.t. materials, given by 29.95%.

Table 3.11: Output shares in % w.r.t. inputs over all firms

			Percentiles		
Output share	Mean	Std Dev	P10	P50	P90
$\widehat{a}^K_{nt}$	7.71	11.22	1.42	5.26	15.47
$\widehat{a}^L_{nt}$	45.35	45.02	17.97	36.55	76.70
$\widehat{a}^M_{nt}$	31.55	18.46	8.66	29.95	55.56

Figure 3.20 shows for the overall French manufacturing the median output shares w.r.t. capital, labor, and material input over time. It can be seen that the output hare w.r.t. labor, given by the dotted line, declines over time, which is a widely observed pattern. The median output share w.r.t. materials, given by the solid line, instead slightly increases while the median output share w.r.t. capital remains relatively constant over time.

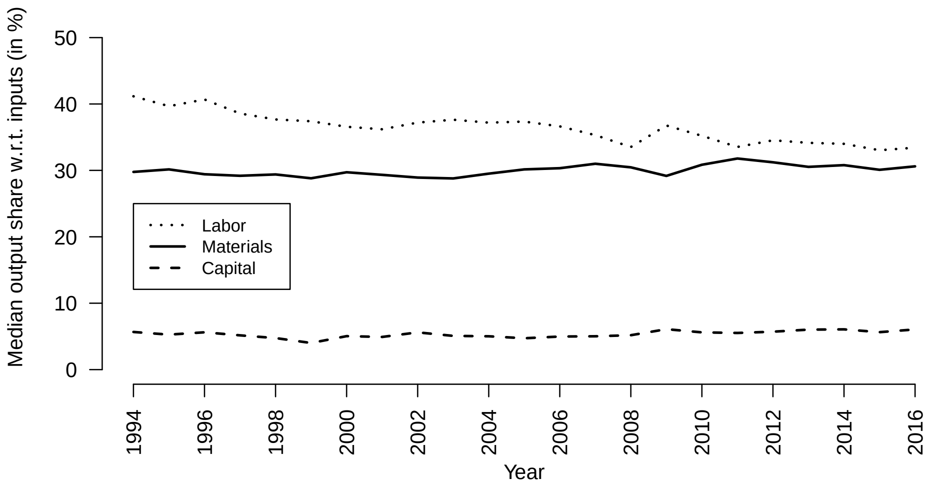

Figure 3.20: Output shares w.r.t. inputs over time

Chapter 4

Cournot equilibrium and welfare with heterogeneous firms[1]

4.1 Introduction

One of the unfortunate consequence of most firm level cost function specifications is their difficulty to yield plausible (optimal) output levels. Heterogeneity in the fixed costs vanish in the derivation of the profit maximizing condition and is useless to generate heterogeneous firm size. Conversely, heterogeneity in the variable cost function is unable to explain why so many small firms make positive profits while others do not. One objective of this chapter is to propose a setup allowing for joint heterogeneities in fixed and variable costs, and enabling to reproduce the observed distribution of firms sizes. Heterogeneous cost functions yield firm and time specific break even points and minimum efficient scale. This in turn characterizes which technologies allow generating positive profits, and identifies those firms which are likely to exit the market as well as potential entrants and survivors. We adopt the Cournot model, with heterogeneous firms interacting strategically and choosing their optimal output level given aggregate output, and further cost and demand parameters.

While the literature on the existence and unicity of Cournot equilibrium often considers industries with identical firms and symmetric equilibrium, there are some interesting exceptions. Novshek (1985) showed that a short-run Cournot equilibrium exists under weak conditions on firms' cost function. Unicity of the short-run Cournot equilibrium with heterogeneous firms was derived by Gaudet and Salant (1991). In the long-run, when firms' entry and exit occurs, Okumura (2015) proved that existence of the Cournot equilibrium still holds. It is, however, no longer unique, and this opens the possibility to investigate whether further Cournot equilibria exists with possibly higher total output and employment. We contribute to this literature and amend the homogeneous firm Cournot model. While our purpose is mainly empirical, we also describe the theoretical implications of heterogeneous

[1]This chapter is based on De Monte, E. and Koebel B. (2021), Cournot equilibrium and welfare with heterogeneous firms, *mimeo, BETA, Université de Strasbourg.*

technologies at the firm level, both on the short- and the long-run Cournot equilibrium. Interestingly, we show that there is a relationship between firm size (in terms of output) and their type of heterogeneous technology.

It is well known that the short-run Cournot equilibrium is generally inefficient. Mankiw and Whinston (1986) have shown that even in the long-run, firms' entry and exit does not necessarily contribute to reduce inefficiency. We extend their result to the case of heterogeneous firms and empirically investigate whether redistributing output over firms allows to increase industry output, reduce total cost and increase efficiency. Especially for France, the stylized facts document that there are many very small firms but a lack of medium sized and large firms. In manufacturing industries, Table 4.1 illustrates that in comparison to Germany, there is roughly the same number of firms with 0 to 9 employees, but only 54% of the number of small firms (with 10 to 49 employees). This rate decreases to about 35% for larger firms with 50 employees and more. Garicano et al. (2016) attribute the lack of medium sized firms in France to laws specific to firms with 50 employees and more, and which prevent firms' to grow above this threshold. This explanation is not sufficient to describe the lack a medium sized and large firms in France and we investigate whether the low number of firms is related to the nature of the market structure and competition in the manufacturing industries. Starting from a long-run Cournot equilibrium, we study whether total industry output is inefficiently allocated to smaller firms with high variable cost instead to bigger firms with low marginal cost.

Table 4.1: Number of active firms and employment by firm size, manufacturing, France and Germany, 2017

			Firm size			
		Total	0-9	10-49	50-249	>250
France	No. of Firms	193,609	162,955	23,468	5,658	1,522
	No. of Employees	2,832,458	259,459	488,990	601,247	1,482,624
Germany	No. of Firms	234,310	170,585	43,540	15,845	4,340
	No. of Employees	7,040,463	336,753	939,166	1,701,813	4,062,731

We use fiscal data for firms which are available for France for the years 1994 to 2016 (FICUS and FARE data). The data comprises the universe of active firms, but we consider only those belonging to the manufacturing industry. We consider 184 industries at the 4-digit aggregation level, within which firms are assumed to produce an homogeneous output and to compete à la Cournot. In a typical 4-digit industry, 0.5 % of all firms hire about 39 % of the employees working in this industry, and produce 56 % of total industry output. The concentration ratio of the 3 and 10 biggest firms are respectively $C_3 \simeq 53\%$ and $C_{10} \simeq 70\%$. These figures document that there are few actors which must have strong market power, and a large competitive fringe of smaller firms. This seems compatible with the theoretical Cournot model adopted here, allowing for technological differences between firms.

Empirically we have to deal with the incidental parameter problem occurring when taking into account heterogeneity over firms and across time in fixed and variable costs: new observations carry with them new heterogeneity terms and do not contribute identifying the model in an obvious way. When heterogeneity is unobserved but correlated with decision variables (the optimal level of output) least squares estimates are inconsistent. We solve this problem by parameterizing the unobserved heterogeneity, and estimating both the inverse output demand function addressed to an industry, the marginal cost condition and the total cost function for each firm. While the inverse demand function is estimated by Generalized Method of Moments (GMM), we are able to estimate the system of cost and optimal output condition by an extended version of ordinary least squares. With Cournot competition, this approach allows to reveal the distribution of unobserved heterogeneity in both the fixed and variable cost. We contribute to the existing empirical literature by introducing explicitly joint heterogeneity in the fixed cost and in the variable cost of production, and studying the interplay between both types of heterogeneity. The existing literature mainly focuses on univariate heterogeneity, either in the variable cost function (Davis, 2006) or in the fixed cost function (Berry, 1992) or in total cost (Esponda and Pouzo, 2019). While these specifications all entail unidimensional heterogeneity in the total cost function, we allow for separate heterogeneity in both the fixed and the variable cost functions. While the theoretical framework for the occurrence of joint heterogeneity and their interdependence is studied by Chen and Koebel (2017), we are not aware of any empirical contributions at the firm level. Another part of the literature tackling the issue of productivity and technological change bases its identification strategy on the production function (Ericson and Pakes, 1995). Adding a firm and time specific effect to the production function, however, imposes strong restrictions on fixed and variable costs. Our cost function based approach allows more flexibility and is compatible with more general specifications of technological heterogeneity.

Section 4.2 presents the heterogeneous firm setup and describes the short-run Cournot equilibrium. Section 4.3 characterizes the long-run equilibrium. The theoretical results pertaining to the inefficiency of the Cournot equilibrium are discussed in Section 4.4, which also describes the welfare maximizing allocation of production over firms. The data and descriptive statistics are presented Section 4.5. Section 4.6 and 4.7 discuss the empirical model along with the estimation strategy and presents the results, and Section 4.8 concludes.

4.2 Short-run Cournot equilibrium with heterogeneous quadratic cost functions

Within each industry firms are competing à la Cournot. In the short-run, there are N active firms facing the same inverse demand function

$$p = P(y_n + \sum_{j \neq n}^{N} y_j), \tag{4.1}$$

where p denotes the output price, y_n the production of firm n and $Y_{-n} \equiv \sum_{j \neq n}^{N} y_j$ the total output of firms' n competitors. We do not introduce subscripts for the industry yet, but it is important to realize that the inverse demand is specific to industry i. We assume that the total cost function of each firm is the sum of a firm specific fixed cost and a variable cost function:

$$c_n(w_n, y_n) = u_n(w_n) + v_n(w_n, y_n), \tag{4.2}$$

where the fixed cost of production u_n depends upon input prices w_n but also upon technological choices and constraints which are specific to firm n. The variable cost function v_n satisfies, by definition, the condition $v_n(w_n, 0) = 0$. Each firm is profit maximizing and chooses its output level according to the first order optimality condition:

$$P(Y) + P'(Y)y_n = \frac{\partial c_n}{\partial y_n}(w_n, y_n) \tag{4.3}$$

where Y denotes the aggregate output level of the industry. Note that if the fixed cost function u_n is heterogeneous but the variable cost function v_n is the same over all firms, then (4.3) implies identical output levels over all firms with the same input prices. Such a model would attribute differences in firm sizes to difference in input prices. Here, heterogeneity in variable costs is helpful to yield optimal individual production levels able to approximate the empirical distribution of firm sizes. The second main advantage of our heterogeneous firm framework, is that it can explain why bigger firms have increasing returns to scale while smaller firms have decreasing returns. In the homogeneous case with U-shaped average cost functions, returns to scale are increasing for production levels smaller than the efficient scale of production and decreasing for larger production levels. This is not necessarily the case here.

We assume the following regularity conditions (that will be empirically investigated later on):

Assumption 1. The inverse demand function P is nonnegative, continuous, differentiable and decreasing in Y.

Assumption 2. The cost function is continuous in w_n and y_n, nonnegative, differentiable and increasing in w_n and y_n.

Assumption 3. There exist firm-level and aggregate production levels $\overline{y}$ and $\overline{Y}$ such that

(i) the marginal revenue is lower than the marginal cost:

$$P\left(Y\right)+P'\left(Y\right)y<\partial c_n/\partial y_n\left(w_n,y\right), \tag{4.4}$$

for any $y>\overline{y}$ and $Y>\overline{Y}$, and any firm $n=1,...,N$;

(ii) the cost function is not too concave:

$$P'\left(Y\right)<\partial^2 c_n/\partial y_n^2\left(w_n,y\right), \tag{4.5}$$

for any $y<\overline{y}$ and $Y<\overline{Y}$, and any firm $n=1,...,N$.

Assumptions 1 and 2 are quite common in microeconomics. Assumption 3(i), implies that there is an upper threshold $\overline{y}$ to individual production (because marginal cost is always higher than marginal revenue for $y>\overline{y}$). A3(ii) forbids the occurrence of highly nonconvex cost functions. Condition A3(ii) is common in the literature on Cournot oligopoly, see Amir and Lambson (2000) for instance. Cournot equilibrium exists under relatively mild conditions, we follow Novshek (1985) who showed existence provided that:

Assumption 4. The marginal revenue function satisfies:

$$P^{'}\left(Y\right)+y_nP^{''}\left(Y\right)\leq 0, \tag{4.6}$$

for any value of $y_n\leq Y<N\overline{y}$.

A1 and A4 imply that the marginal revenue function is decreasing. A4 together with the second order condition for profit maximization imply that firms' reaction functions are downward sloping. Gaudet and Salant (1991) have shown that A1-A4 imply the uniqueness of Cournot equilibrium. Amir (1996, Corollary 2.2) used another condition implying the existence of Cournot equilibrium which is not equivalent to A4. A4, however, was found to be more useful for deriving some results below.

We follow Novshek (1984) and consider the backward reaction functions as the solution in $y_n\geq 0$ to the system of N equations (4.3), for given values of aggregate output Y and input prices w_n:

$$y_n^b(w_n, Y). \tag{4.7}$$

Assumptions 3(ii) and 4 guarantee that the backward reaction functions are nonincreasing in Y. Given existence, we then characterize Cournot's equilibrium as the solution to the equation

$$Y = \sum_{n=1}^{N} y_n^b(w_n, Y), \tag{4.8}$$

which guarantees that all firms projections about aggregate output are fulfilled at equilibrium. We denote the equilibrium by Y^N, and $y_n^N = y_n^b(w_n, Y^N)$ and note that these functions depend upon the characteristics of all firms active in the industry.[2] We have the following interesting implications:

Proposition 1. Under A1-A4, at the Cournot equilibrium with fixed number of firms,
(i) The elasticity of inverse demand $\epsilon(P,Y)$ satisfies $-N < \epsilon(P,Y) < 0$
(ii) Firm's n market share satisfies $y_n^N/Y < -1/\epsilon(P,Y)$
(iii) The value of the marginal cost of production decreases with firm size
(iv) The price markup increases with firm size.
(v) For a subset of $N' < N$ active firms, $Y^{N'} < Y^N$ and $y_n^{N'} > y_n^N$.

Proposition 1 restates several claims that are well known to researchers working in the field of Cournot equilibrium with heterogeneous firms, but often not to be found in textbooks considering mainly homogeneous firms. It follows from Proposition 1, that if we order firms by size (say from the smallest to the biggest), this implies that the same order carry over to the markup and the reverse ordering applies to marginal cost. P1(v) corresponds to what Mankiw and Whinston (1986) refers to as the business-stealing: new entries contribute to increase total output but reduce individual production levels of incumbents. In the context of heterogeneous firms, this result is derived by Okumura (2015, Lemma 1).

Equality (4.3) also implies an interesting relationship between firms' profit rate, the inverse demand elasticity and the rate of returns to scale:

$$\frac{py_n^N - c_n}{c_n} = \frac{1}{1 + \epsilon\left(P;Y\right) y_n/Y} \epsilon\left(c_n; y_n\right) - 1. \tag{4.9}$$

Ceteris paribus, the higher the rate of return to scale $1/\epsilon\left(c_n; y_n\right)$, the lower the profit rate; the higher the market share y_n/Y, the higher the profit rate. Equation (4.9) also implies that

[2] The superscript N denotes both Nash equilibrium, and the fact that the number of firms is kept constant (no entry, no exit) here.

for a firm with positive profit there is a lower bound for its market share given by

$$\frac{y_n^N}{Y^N} \geq \frac{\epsilon\,(c_n; y_n) - 1}{\epsilon\,(P; Y)}.$$

Hence, firms with increasing returns to scale must have sufficient market share in order to have positive profits.

We rewrite the cost function in order to highlight the two parameters γ_n^u and γ_n^v which deform the functions u and v which are common to all firms:

$$c_n(w_n, y_n) = \gamma_n^u u(w_n) + \gamma_n^v v(w_n, y_n). \tag{4.10}$$

While actually any cost function (4.2) can be written this way, we now restrict firm heterogeneity to be stochastic:

Assumption 5.
(i) The parameters γ_n^u and γ_n^v are stochastic and exogenous to the firm.
(ii) Firms know their technology $\gamma_n = (\gamma_n^u, \gamma_n^v)$ before producing and competing à la Cournot.

A5 ensures that the heterogeneity terms are not a function of further explanatory variables of the cost function, that they are exogenous to the firm, in the sense that they do not (systematically) change with w_n, y_n. This assumption can be justified by the fact that the choice of the technology is made just before the firm first entered the market, and the current value of γ_n^u and γ_n^v are considered as (conditionally) random technological shocks. Note that an increase in γ_n^u or γ_n^v corresponds to a negative technological shock while a decrease in these parameters represents technological progress. More restrictive versions of A5 are found in the literature, assuming either that $\gamma_n^u = 0$ (Jovanovic, 1982), $V[\gamma_n^u] = 0$ (Hopenhayn, 1992), γ_n^v iid (Jovanovic, 1982), γ_n^v independent of γ_n^u (Bresnahan and Reiss, 1991). We aim to stay general in following our purpose of estimating the joint distribution of γ. The variable cost heterogeneity parameter γ_n^v is related to the additive TFP term ω_n often considered in the context of production. It can be shown that when v is linearly homogeneous in y then $\gamma_n^v = 1/\exp(\omega_n)$.

Figure 4.1 represents five zones in which different types of firms can be located. In zone I, firms exhibit higher than average variable costs and relative low fixed costs. These type of firms can enter or exit the market without bearing high sunk cost. Zone II corresponds to a zone of generalized inefficiency: firms exhibit both higher fixed and variable costs. Firms located in zone III are extremely efficient and able to produce with fixed and variable costs lower than average. Zone IV comprises firms producing with lower than average variable costs and higher fixed costs. In zone V, firms operate with an average technology and are similar to a representative firm characterized by $E[\gamma^u] = E[\gamma^v] = 1$.

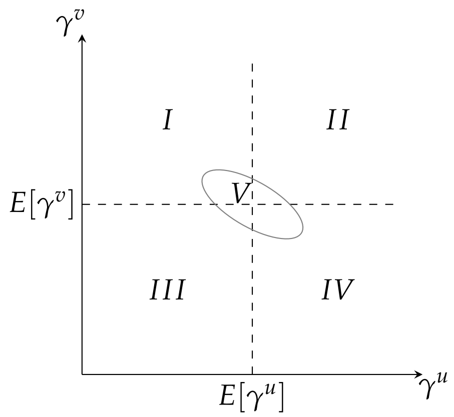

Figure 4.1: Five technological zones

In each different zone depicted on Figure 4.1, firms are not only different w.r.t. their technology, but we also expect to see difference in the levels of the endogenous variables.

Proposition 2. Under A1-A5, at the short-run Cournot equilibrium with fixed number of firms,
(i) firm i individual production level decreases with γ_i^v,
(ii) firm i production level increases with γ_j^v,
(iii) the aggregate equilibrium level of production decreases with γ_i^v,
(iv) individual and aggregate production levels are unaffected by a change in γ_i^u.
(v) firm i profit decreases with γ_i^v and γ_i^u;
(vi) firm i profit increases with γ_j^v.

This result, proven in Appendix 4.9, follows (as usual) from the first and second order optimality conditions and the fact that the marginal cost function is positive. Related results for input demands have been derived by Koebel and Laisney (2014). For output supply, Février and Linnemer (2004) derive a similar result, but for the case of constant marginal costs. It is intuitive that an increase in firm i's marginal cost (through higher γ_i^v) decreases its output, but quite messy to prove due to firm heterogeneity and the existence of aggregate Cournot effects in the backward reaction functions. According to this result, we expect to see bigger firms located in zone III or IV of Figure 4.1. It is noteworthy (P2ii) that despite the output level of all competing firms decreases after a favorable productivity shock on i, the aggregate Cournot output is increasing, too (P2iii). This means, cost reducing technological change hurts firms that are not affected by it, which loose market shares, but aggregate production in the industry increases. The increase in market size outweighs the redistributional effect in the market shares.

Assumption A5 does not introduce any restriction about the relationship between γ_n^u and γ_n^v, and we considered in P2 that both variables could be shifted independently the one from the other. We now introduce a form of interrelation between them. The parameter γ_n^v reflects the efficiency of the variable cost function, the lower it is, the better for the firm. Conversely, the parameter γ_n^u is often considered as an inefficiency, increasing the level fixed cost. However, from microeconomic theory, we know that it is likely that a higher fixed cost usually allows a firm to produce at a lower marginal cost, at least for some range of the output level. See for instance Chen and Koebel (2017) for the theoretical foundations and an empirical investigation. Let us restate this relationship explicitly:

Assumption 6. The variable cost efficiency is a decreasing transformation of the fixed cost efficiency:

$$\gamma^v = e(\gamma^u) + \eta, \tag{4.11}$$

with function e decreasing and the random term η iid, with an expectation equal to zero, constant variance and uncorrelated with γ^u.

Function e transforms the firm specific fixed cost efficiency γ_n^u into a variable cost efficiency γ_n^v characterizing firm n's production technology. It is identical for all firms (within an industry), because e represents the mean technological frontier between the different types of production possibilities. A6 implies that, on average, technological progress is not transmitted through simultaneous reductions in both cost parameters γ_n^u and γ_n^v, but there is a trade-off characterized by e. A6 has an interesting empirical implication:

$$cov(\gamma_n^u, \gamma_n^v) < 0. \tag{4.12}$$

This inverse relationship between fixed and variable costs is often neglected in international trade (compare with Melitz (2003) or industrial economics (see for instance Bresnahan and Reiss (1991)), where fixed costs are often considered as a pure inefficiency. We will test whether this assumption or instead our more general version stated in A6 is satisfied or not. For our empirical investigation, we assume that firms have quadratic cost functions:

Assumption 7. The variable cost function is assumed to be quadratic in production:

$$v(w_n, y_n) = v_1(w_n)y_n + \frac{1}{2}v_2(w_n)y_n^2. \tag{4.13}$$

The quadratic specification of the cost function stated in A7 is compatible with the criteria of local flexibility of the cost function, which is shown to be important for empirical investigations (Diewert and Wales, 1988). The family of cost functions defined by (4.10) and (4.13) is able to approximate a variety of cost functions usually considered in the literature. We introduce two multiplicative firm specific terms γ_n^u and γ_n^v to capture heterogeneity over firms, in both their levels of fixed and variable costs. Specification (4.10), (4.13) generalizes the heterogeneous fixed cost specification of Spulber (1995) (who sticks to the constant marginal cost assumption). It also extends the heterogeneous (but constant) marginal cost specification of Bergstrom and Varian (1985) and of Salant and Shaffer (1999).

The firm specific average cost function is U-shaped if $u_n > 0$ and $v_{2n} > 0$ and reaches its minimum for production level $\underline{y}_n = \sqrt{2\gamma_n^u u/(\gamma_n^v v_2)}$. The efficient scale of production can therefore be different from one firm to the other. The quadratic specification is convenient as it allows to obtain an explicit solution for Cournot's equilibrium in terms of (nonnegative) individual and aggregate production levels:

$$y_n^b(w_n, Y) = \frac{P(Y) - \gamma_n^v v_1(w_n)}{\gamma_n^v v_2(w_n) - P'(Y)}, \tag{4.14}$$

$$Y^N = \sum_{n=1}^{N} y_n^b(w_n, Y^N). \tag{4.15}$$

This highlights that the firm level of production at the equilibrium $y_n^N = y_n^b(w_n, Y^N)$ does not only depend upon aggregate output and input prices, but also upon the choice of the technology captured by γ_n^v. Equation (4.14) also illustrates that *ceteris paribus*, the higher the variable cost the lower the production level y_n^N (see P2iii).

Proposition 3. Under A1-A7, we consider two firms at Cournot equilibrium, both with similar input prices w. Assume that the cost functions are convex. The Nash equilibrium production levels of firms i and j satisfy $y_i^N < y_j^N$ iff
(i) the biggest firm is more productive: $\gamma_i^v > \gamma_j^v$
(ii) the biggest firm has a lower variable cost for each unit produced: $v_i\left(w, y_i^N\right)/y_i^N > v_j\left(w, y_j^N\right)/y_j^N$
(iii) on average, bigger firms have higher fixed costs: $\mathrm{E}\left[\gamma_i^u\right] < \mathrm{E}\left[\gamma_j^u\right]$ and $\mathrm{E}\left[u_i\left(w\right)\right] < \mathrm{E}\left[u_j\left(w\right)\right]$;
(iv) on average, bigger firms have a larger efficient scale of production.

P3 implies that when firms are heterogeneous in their technologies, these differences induce them to choose different operating sizes, yielding a relationship between firms' production level and their technological characteristics. If we order firms along their output level (from the smallest to the biggest), there is equivalently a corresponding ordering of the technological parameters γ^v and the variable unit cost of production. For the fixed costs and the efficient scale of production, the ordering is not perfect, but subject to random errors in the relationship between fixed and variable costs. On average, however, the order is preserved. The aggregate production Y^N implicitly defined in (4.15) also depends upon the number N of active firms, we now study entry and exit and how adjustment in N affects the main results of this section.

4.3 The long-run Cournot equilibrium

We now characterize a long-run Cournot equilibrium (LRCE) as a short-run Cournot equilibrium in which the number of active firms adjusts to exhaust expected profit opportunities. Firms choose either to enter or exit the market using available information. We denote by $\mathcal{N}$ the set of firms indices which are active, and by $\mathcal{M}$ the set of firms' indices which are inactive. The LRCE corresponds to a game in which firms choose their activity and production levels simultaneously, see Lopez-Cuñat et al. (1999) who also compares the simultaneous game with the one where entry and production choices are sequential. Active firms incur a fixed cost $c_n\left(w_n, 0^+, \gamma_n\right) = u_n\left(w_n\right)$ and inactive firms have $c_n\left(w_n, 0, \gamma_n\right) = 0$. Active firms expect nonnegative profits and all potential entrants expect nonpositive profits. Conditionally on observables, the cost function is subject to randomness due to unknown technological progress at the beginning of the period (see A5). It turns out that aggregate production, individual production, and profits are also random, hence, the entry/exit condition defining the LRCE is given by

$$E\left[P\left(Y_n^N\right) y_n^N - c_n\left(w_n, y_n^N\right)\right] \geq 0, \tag{4.16}$$

$$E\left[P\left(Y_n^N + y_m\right) y_m - c_m\left(w_m, y_m\right)\right] \leq 0, \tag{4.17}$$

for any $n \in \mathcal{N}$ and $m \in \mathcal{M}$. The expectation operator E denotes the (rational) expectation with respect to the technological shocks γ_n which are random (and whose distribution includes information available to the firm at time of decision). Okumura (2015, Theorem 1) showed that under A1-A4 the LRCE with heterogeneous firms exists. The equilibrium is not unique however: different histories condition the expectations in (4.16) and (4.17). In this respect, we follow Novshek (1984) and Okumura (2015) and consider that firms cannot change their technology without further cost. Conditionally on observables, differences in the technology over firms (and time) is random (see A5). This is different from Götz (2005) and Ledezma (2021) who consider that firms can choose their production technology optimally and without adjustment cost. In this context, only the more efficient technologies are chosen, with the consequence that, at equilibrium, firms tend to be similar in technology and firm size. It would be quite a challenge with this approach to endogenously generate a distribution of firms' sizes close to those usually observed in a given industry.[3] Note that the density function of the technological shock is firm specific: entering firms are drawing γ_{nt} from a different distribution than firms which already have 20 or 40 years of activity and have reached some size.

Whether conditions (4.16) and (4.17) are satisfied by the data is an empirical question. For this, we need to characterize entering and exiting firms and empirically determine the distribution of sizes and technologies of entering and exiting firms. We could for example simulate fictive firms entering the market, by resampling technologies γ_n from the list of entering firms and replicate the Cournot economy with N_r firms instead of N. Similarly, we could also simulate exiting firms by resampling from the technologies of the group of firms with negative profits. The procedure stops when entering/exiting firms have 50% chance to make a negative profit. Doing this we discard general equilibrium effects arising from eventual shifts in the aggregate output demand function (occurring when profits and loss are redistributed to consumers), and we consider that the demand function is fixed, while the aggregate supply function changes.

4.4 The welfare consequences of entry and exit at LRCE

We now consider the welfare implications of the observed distribution of output and investigate, following Mankiw and Whinston (1986) the welfare loss at LRCE. In a setup with identical firms, Mankiw and Whinston have shown that under business stealing (see P1v), the free entry equilibrium leads too many firms to enter the market in comparison to what is optimal from the welfare viewpoint. This result has been extended by Amir et al. (2014) to a setup where the planer controls either entry (but not production) or entry and production. In our situation with heterogeneous firms, the central planer has to carefully consider technological differences when deciding which firm is allowed to produce and how much. We assume that she knows the technological parameters γ_n of each firm, and decides upon their activity and production levels to maximize welfare. The welfare optimizing individual and aggregate productions are denoted by y_n^W and Y^W. The welfare function is similar to the one of Mankiw and Whinston (1986):

$$\begin{aligned} W\left(y_1, \ldots, y_M\right) &= \int_0^{\sum_{m=1}^M y_m} P\left(s\right) ds - \sum_{m=1}^M c_m\left(w_m, y_m\right), \qquad (4.18) \\ y_m &\geq 0. \end{aligned}$$

[3]We are aware that even in a setup with homogeneous firms, we can end up with asymmetric Cournot equilibrium, see for instance Novshek (1984). The corresponding distribution of firm sizes is very restrictive, however.

Note that all M firms are considered as potential contributor to economic activity in W. The planer has also to decide whether $y_m^W > 0$ or $y_m^W = 0$ and the discontinuity of the cost function at $y_m = 0$ has to be treated carefully. We proceed as follow.

In a first step, we define the continuous extension $\widetilde{W}$ of W over $[0, \overline{y}]^M$ as

$$\widetilde{W}(y_1, \ldots, y_M) = \int_0^{\sum_{m=1}^M y_m} P(s)\, ds - \sum_{m=1}^{M} \widetilde{c}_m(w_m, y_m),$$

where $\widetilde{c}$ is the continuous extension of c over $[0, \overline{y}]$:

$$\widetilde{c}_n(w_n, y_n) = u_n(w_n) + v_n(w_n, y_n).$$

Now, the extended cost function satisfies $\widetilde{c}_n(w_n, 0) = u_n(w_n)$ at $y_n = 0$ and for $y > 0$, $\widetilde{c}_n(w_n, y_n) = c_n(w_n, y_n)$. We apply the Kuhn and Tucker optimization techniques to $\widetilde{W}$ which yield a first interesting set of solutions $\{\widetilde{y}_m\}_{m=1}^M$. All inner solutions of (4.18) correspond to those of $\widetilde{W}$, but $\widetilde{y}_m > 0$ does necessarily imply that $y_m^W > 0$ as the social planer should still investigate whether it is really welfare improving to let firm m producing something at all. The main problem with maximizing $\widetilde{W}$, is that the solutions are unaffected by the amount of the individual fixed costs (this is directly seen by looking at the Kuhn and Tucker first order conditions for optimality). This is the only reason why the arguments maximizing $\widetilde{W}$ do not necessarily maximize W. However, the artificial function $\widetilde{W}$ is helpful, because all positive production plans which are not maximizing $\widetilde{W}$ will not maximize W either, and can be discarded.

In a second step, we characterize the necessary condition for a social planer to allow firm n to be active at the long-run welfare maximizing point (LRWP). Positive production of firm n improves welfare if the consecutive increase in consumer surplus exceeds the cost of producing y_n^W. This is the case at Y_{-n}^W if

$$\int_0^{y_n^W} P\left(Y_{-n}^W + y\right) dy - c_n\left(w_n, y_n^W\right) \geq 0. \tag{4.19}$$

If this inequality is satisfied then $y_n^W = \widetilde{y}_n > 0$, and else $y_n^W = 0$. This necessary condition for a social planer to allow firm n to enter the market is interesting in comparison to the LRCE condition of positive profits. As $P \geq 0$ and decreasing, it can be seen that $\pi_n^W \geq 0 \Rightarrow$ (4.19), the converse however is not true and the social planer improves welfare by letting some specific firms with negative profits into the market.

The first order Kuhn and Tucker necessary conditions for an inner maximum for W are:

$$P\left(\sum_{m=1}^{M} y_m\right) = \frac{\partial c_n}{\partial y_n}(w_n, y_n) - \lambda_n, \qquad \lambda_n \geq 0, \qquad \lambda_n y_n = 0, \tag{4.20}$$

for $n = 1, \ldots, M$. It follows that a welfare maximizer:

(i) sets the production level of active firms to equalize price and marginal cost ($\widetilde{y}_n > 0 \Rightarrow \lambda_n = 0$).[4]

(ii) shuts down any firm with a marginal cost above the price: if $\partial c_m / \partial y_m (w_m, y_m) > P(Y_{-m} + y_m)$ for any y_m then $\lambda_m > 0$ and $\widetilde{y}_m = 0$.

(iii) shuts down any firm with a negative net contribution to welfare:

$$y_n^W = \begin{cases} \widetilde{y}_n & \text{if } (4.19) \\ 0 & \text{else} \end{cases} .$$

A3(ii) ensures that W is concave in y_n at $y_n^W > 0$, and that the above first order conditions is sufficient for y_n^W to maximize W. Condition (4.20) requires that at the optimum, all active firms produce with the same marginal cost, which contrasts with LRCE at which active firms are characterized by a price above their firms' marginal cost. Some firms active at the LRCE will no longer be active at the LRWP: a lower price $P(Y^W) < P(Y^C)$ calls for lower marginal cost by (4.20), but firms producing less and having few market power, will typically have difficulties to cope with this requirement. It also follows from (4.20) that at the social optimum, active firms with positive profits exhibit (local) decreasing returns to scale: $Py_{nt}/c > 1 \Leftrightarrow \varepsilon(c; y) > 1$ (and firms with negative profits have increasing returns). We state a result extending this of Mankiw and Whinston (1986) in a setup with heterogeneous firms.

Proposition 4. Assume A1-A5. In comparison to the LRWP, the LRCE is characterized by
(i) a lower aggregate production and a higher price: $Y^C < Y^W$ and $P(Y^C) > P(Y^W)$
(ii) profits which are too high: $\pi_n^C > \pi_n^W$
(iii) big firms which produce too little, $y_n^C < y_n^W$
(iv) small firms with global decreasing returns which produce too much: $y_n^C > y_n^W$, and some of them should be shut down
(v) small firms with increasing returns which either produce too little, or should be shut down
(vi) a subset of the firms active at LRCE is still active at the LRWP.

The proof of P4 (see Appendix 4.9) is constructive in the sense that it characterizes which firm is producing more and which one will be inactive at LRWP. It also defines a big firm as a firm with a level of production at LRCE such that its marginal cost of production

[4] Conversely, however, some inactive firms ($\lambda_m = 0$) would be able to cope with condition (4.20), but at a too high fixed cost, so that the planer assigns them $y_m^W = 0$ in the second step.

is too low for welfare maximizing:

$$\frac{\partial c_n}{\partial y}\left(w_n, y_n^C\right) < P\left(Y^W\right),$$

and conversely for a small firms. This result is also useful for our empirical purpose of simulating firms' size distribution at the LRWP. We use P4 to code the algorithm calculating the increase in aggregate production and the corresponding reallocation of output over firms at the LRWP. Contrary to Mankiw and Whinston (1986), firms are differently affected by the new pricing rule, however, most results they obtain in the homogeneous firms case carry over to an economy with heterogeneous firms. Instead of centralizing all production decisions, the central planer can equivalently introduce a tax and subvention scheme for inciting firms to produce at the socially optimal level. Comparing the conditions (4.20) and (4.3) we see that the aggregate production level of Y^W can be decentralized through the introduction of a sale tax τ specific to each firm and given by:

$$\tau_n(y) = \left|1 - \frac{P(Y^W)}{P(Y_{-n}^C + y)}\right|.$$

Note that the sale tax rate is decreasing in y at LRCE and takes a value of zero at the LRWP. See Guesnerie and Laffont (1978) for related results. An interesting consequence of P4 is the following:

Proposition 5. Under A1-A7, we consider firms with similar input prices w at Cournot equilibrium. Assume that the cost functions are convex. Then $N^W \leq N^C$ and the Hirschman-Herfindahl index of concentration is higher at the LRWP than at LRCE.

P5 means that an efficient industrial policy should not try to minimize industry concentration at all costs. Actually, the opposite policy would improve welfare in the case of Cournot competition. A related corollary has been proposed by Salant and Shaffer (1999, Corollary 2), but for a situation where aggregate production stays constant. We generalize their result to the comparison of two situations with different levels of aggregate output since $Y^W \geq Y^N$. The economic intuition behind the result is as follows: for given N the Cournot equilibrium price is too high, $P^N\left(Y^N\right) \geq P^W\left(Y^W\right)$, and incites small and inefficient firms to enter the market, while for welfare maximization the planer prefers to increase the production of the technologically more efficient firms. Free entry decreases the long run Cournot prices such that at the LRCE there is no incentives for an efficient and potentially big firm to enter the market. The proof of P5 is provided in Appendix 4.9, and is both a consequence of the properties of the Hirschman-Herfindahl index, than of P4, which states that the LRWP is achieved through redistribution of output from the socially inefficient and smaller firms to the efficient and bigger firms. We, however, need to focus on convex technologies in order to exclude the occurrence of P4(v). We also reduce the dimension of heterogeneity sources and assume identical input prices. By continuity in w, P5 still applies if input prices are close enough but not strictly identical for firms n and m. In an economy with heterogeneous firms, the social planer prefers to see some specific types of firms producing, and other not to be active. Firms allowed to produce are characterized by:

$$\Gamma^W = \left\{ (\gamma_n^u, \gamma_n^v)_{n=1}^M : (4.19) \right\} \tag{4.21}$$

We will represent this technological activity-frontier for the LRWP and compare it to the LRCE set:

$$\Gamma^C = \left\{ (\gamma_n^u, \gamma_n^v)_{n=1}^M : (4.16), (4.17) \right\}. \tag{4.22}$$

Whether and by how much free entry leads to an excessive number of firms and a too low aggregate production is an empirical question which is studied below. With heterogeneous firms, we expect to find a result in between the extreme cases handled in the literature. Free entry should be socially less beneficial than in competitive models (with heterogeneous firms but no market power), and less harmful than in homogeneous firms models with markups and fixed costs.

4.5 Data and descriptive statistics

We use French fiscal data available at the firm-level for the years 1994 to 2016 (FICUS and FARE data).[5,6] The data comprises the universe of active firms, but we consider only those belonging to the manufacturing industry.[7] The observations contain information on firms' balance sheet and income statements, where each firm is identified by a specific identification number, which is constant over time. Table 4.2 provides a description of the included manufacturing sectors with the corresponding number of firms and observations. After a basic data cleaning the treated sample comprises in total 176,640 firms summing up over time to 1,455,383 observations.

[5] FICUS and FARE refer to "fichier de comptabilité unifié dans SUSE" and "fichier approché des résultats d'Esane", respectively. That is, FICUS was part of the French firm-level database SUSE and was replaced in 2008 by FARE that, in turn, belongs to the current database Esane.

[6] See Chapter 2, Appendix 2.9 for more information on the construction of the dataset.

[7] We exclude the industry for food processing (10), the manufacture of tobacco products (12), and the manufacture of coke and refined petroleum products (19). The industry 10 is excluded as it comprises the overwhelming part of the total number of firms and should, in our view, be treated separately. The industries 12 and 19 are excluded for the reason of a very low number of observations. See more details in Appendix 4.10.

Table 4.2: Description of 2-digit industries

Industry[a]	Description	# Firms[b]	# Obs.[c]
11	Beverages	3,031	26,049
13	Manufacture of tobacco products	7,012	59,299
14	Manufacture of wearing apparel	15,658	82,221
15	Manufacture of leather and related products	3,054	22,220
16	Manufacture of wood and of products of wood	13,220	109,643
17	Manufacture of paper and paper products	2,825	28,447
18	Printing and reproduction of recorded media	21,799	174,024
20	Manufacture of chemicals and chemical products	5,204	47,581
21	Manufacture of basic pharm. products and pharm. preparations	979	8,522
22	Manufacture of rubber and plastic products	8,801	86,595
23	Manufacture of other non-metallic mineral products	11,668	95,613
24	Manufacture of basic metals	2,042	18,767
25	Manufacture of fabricated metal products	34,397	326,264
26	Manufacture of computer, electronic and optical products	7,388	57,119
27	Manufacture of electrical equipment	5,033	42,623
28	Manufacture of machinery and equipment	13,362	111,735
29	Manufacture of motor vehicles, trailers and semi-trailers	4,013	35,857
30	Manufacture of other transport equipment	1,799	12,852
31	Manufacture of furniture	15,355	109,952
	Total	176,640	1,455,383

a) Statistical classification of economic activities in the European Community, Rev. 2 (2008)

b) # Firms describes the number of firms which were active over the period (it is computed as the total number of different firms identifiers).

c) # Obs. describes the total number of observations.

Variables

Firm specific data are mainly nominal values and cover the value of production, total labor costs, the value of intermediate inputs, as well as the capital stock. Firms' nominal production is measured by the sum of firms' sales, stocked production, and production for own use. The value of intermediate inputs is given by firms' expenditures for raw materials and other intermediary goods. As proxy for firms' capital stock we use the amount of tangible assets reported in the balance sheet. We use industry specific price indices (at a 2-digit aggregation level) in order to convert the nominal values in real terms.[8] The wage level is firm specific and is obtained by dividing the labor costs by the number of employees. These calculations yield the firms' total production y_{nt}, and input vector $x_{nt} = (x_{k,nt}, x_{l,nt}, x_{m,nt})^\top$ as well as price indices p_{nt} for output and inputs $w_{nt} = (w_{k,nt}, w_{l,nt}, w_{m,nt})^\top$. In order to calculate the user cost of capital, $w_{k,nt}$, we follow Hall and Jorgenson (1967) and set $w_{k,t} = w_{i,nt}(1 + r_t) - w_{i,n,t+1}(1 - \delta_{nt})$, with $w_{i,nt}$ denoting the price index for investment (available at the industry level), r_t is the long-run rate of interest and δ_{nt} the annual rate

[8]The sectoral price data are available at https://www.insee.fr/fr/statistiques/2832666?sommaire=2832834, (April, 2021).

of capital depreciation.[9] Note that, for our purpose, we only keep those firm observations with values larger than zero in capital stock, number of employees, intermediate inputs, and production.

Descriptive statistics

Table 4.3 shows the average number of firms active in a typical 4-digit industry, as well as the distribution of firm sizes over the 1994-2016 period. In our cleaned sample, over all industries and years, there are about 176,640 firms active in the French manufacturing, which represent 1,455,383 observations. At the 4-digit level the number firms is obtained by dividing the total number of observations by 184×23 (the number of 4-digit industries times the number of years), which yields an average number of 340 active firms. See Appendix 4.10 for further details on the data cleaning. The table also reports the average number of firms by different firm size (measured by the number of employees). It shows that the number of firms globally is decreasing in firm size. On average, most firms have between 2 to 4 employees, representing a share of about 24% of all firms. Table 4.3 also informs about market concentration in a typical 4-digit industry: firms with less than 20 employees represent about 75% of all firms, and produce only 7% of total production, whereas the few firms with 500 employees and more produce about 53.1% of the aggregate (4-digit) production. These figures not only document that there are few actors detaining strong market power, but also that there is a large competitive fringe of smaller firms. In our view, this seems compatible with the theoretical Cournot model adopted here, which allows for unobserved technological differences between firms. This unobserved heterogeneity is important for yielding a size distribution of firms endogenously, and comparable with the observed distribution reported on Table 4.3.[10]

[9] The interest rate was provided by the Banque de France, available at https://www.banque-france.fr/statistiques/taux-et-cours/taux-indicatifs-des-bons-du-tresor-et-oat, (April, 2021). We calculate δ_{nt} at the industry level by considering the ratio between the consumption of fixed capital and fixed capital, available at www.insee.fr/fr/statistiques/2383652?sommaire=2383694, (April, 2021).

[10] See also Table 4.12 in Appendix 4.10, which is complementary to Table 4.3, and shows the same statistics but for each 2-digit industries.

Table 4.3: Statistics by firm size in a typical 4-digit manufacturing industry[a]

Firm size[b]	# of firms	Share of firms	Share of employees	Share of production
1	50	14.71	0.40	0.28
2-4	82	24.12	1.86	1.05
5-9	73	21.47	3.93	2.19
10-19	52	15.29	5.67	3.56
20-49	49	14.41	12.29	9.14
50-99	16	4.71	8.83	6.91
100-199	9	2.65	10.76	9.28
200-499	6	1.76	14.83	14.47
500+	3	0.88	41.43	53.11
Total	340	100.00	100.00	100.00

[a] All figures represent averages over all 4-digit industries and years (1994-2016). Shares are given in %.
[b] Firm sizes are measured by the number of employees.

4.6 Inverse output demand estimates

This section studies the output demand addressed to an industry $i = 1, \ldots, I$, and estimates the elasticity of output demand w.r.t. its price. It corresponds to the inverse function of (4.1). The output price index is available at the 2-digit industry level, for $I = 22$ industries, and for the same time range of 24 years as in our firm level data. For the estimation, 2 years are lost due to differencing (and so $T = 22$ years).

We consider the following parametric specification for the output demand to industry i:

$$\ln Y_{it} \quad = \quad \alpha_i + \alpha_Y \ln Y_{i,t-1} + \alpha_p \ln P_{it} + \alpha_{IM} \ln P_{it}^{IM} + \epsilon_{it}. \tag{4.23}$$

In addition to the (domestic) product price P_{it}, we include as regressor the price index P_{it}^{IM} for the imports of the corresponding goods which are close substitutes to domestic products. Industry fixed effects α_i are included, and, as adjustment of demand to the prices may not be instantaneous but under the influence of the lagged level of aggregate quantities, the variable $\ln Y_{i,t-1}$ is also taken in account. Further variables influencing demand are the economy wide GDP, unemployment rate and demographic variables. All these variables are not industry specific and could be captured by the time dummies (as in Koebel and Laisney (2016)). With only a 484 observations however, we choose not to overparameterize our model and consider the more parsimonious specification with 22 industry specific fixed effects and 3 parameters. The elasticity of demand w.r.t. domestic product price is then given by α_p.

The industry specific effect can be correlated with the explanatory variables and the random term ϵ_{it} is correlated with $\ln P_{it}$ since in the aggregate product price adjusts to shocks. We eliminate the industry specific effect by differencing over time:

$$\Delta \ln Y_{it} = \alpha_Y \Delta \ln Y_{i,t-1} + \alpha_p \Delta \ln P_{it} + \alpha_{IM} \Delta \ln P_{it}^{IM} + \eta_{it}, \tag{4.24}$$

with $\eta_{it} = \Delta\epsilon_{it}$.

Several variables that shift the output supply (but not directly output demand) can be considered as instruments: they are correlated with $\ln P_{it}$ and uncorrelated with the random term η_{it}, so that $E[\eta_{it} z_{it}] = 0$. The $(L \times 1)$ vector z_{it} of instruments includes industry labour cost, the price of intermediate consumption, of exports and the price index of imports. Lagged values of the endogenous variables are also considered as exogenous. For each period, we include up to 3 lag values of $\ln P_{it}$ and $\ln Y_{i,t-1}$ in the list of instruments. This gives us a total of $L = 130$ instruments. Given a $(L \times L)$ weighting matrix $\mathbf{W}$, the GMM estimator is defined by minimizing in α:

$$\left(\sum_{i=1}^{I} \sum_{t=1}^{T} \eta_{it} z_{it}^{\top} \right) \mathbf{W} \left(\sum_{i=1}^{I} \sum_{t=1}^{T} z_{it} \eta_{it} \right) = \eta^{\top} \mathbf{ZWZ}^{\top} \eta \tag{4.25}$$

The random terms η_{it} and η_{js} are likely to be correlated, both between industries (which are interdependent) and within a given industry over close time periods. So we use two-ways clustering and allow for heteroscedasticity and for both contemporaneous dependence between residuals of different industries, and for temporal dependence within a given industry when periods are not too distant. See for instance Cameron and Miller (2015) for details about multi-ways clustering and Cameron et al. (2011) for a detailed discussion in the context of GMM. More formally, we assume that

$$\begin{aligned}
&E\left[\eta_{is}\eta_{it}\right] = \sigma_{iist} \text{ for } |s-t| \leq 10,\\
&E\left[\eta_{it}\eta_{jt}\right] = \sigma_{ijtt},\\
&E\left[\eta_{is}\eta_{jt}\right] = \sigma_{ijst} = 0, \text{ for } i = j \text{ and } |s-t| \geq 11 \text{ and for } i \neq j \text{ and } |s-t| \geq 1.
\end{aligned}$$

As there is no possibility to consistently estimate these parameters, we are instead looking to consistently estimate the variance matrix $V[\widehat{\alpha}]$ of dimension $K \times K$. It is convenient to define the set $\mathcal{S}$ of indices of the dependent random terms:

$$\mathcal{S} = \{i, j, s, t : (i = j, |s-t| \leq 10) \vee (i \neq j, s = t)\}.$$

The cardinality of this set is $(I-1)(T+10)T/2 + I(I-1)T = 17908$ and increases with I and T. The GMM weighting matrix is estimated in a first step (using IV estimates $\widehat{\eta}_{it}$) by the inverse of

$$\widehat{\mathbf{B}} = \sum_{i=1}^{I}\sum_{j=1}^{I}\sum_{s=1}^{T}\sum_{t=1}^{T} z_{is} z_{jt}^{\top} \widehat{\eta}_{is} \widehat{\eta}_{jt} \mathbf{1}_{[i,j,s,t \in \mathcal{S}]},$$

where the dummy variable $\mathbf{1}_{[i,j,s,t \in \mathcal{S}]} = 1$ if the indices are included in the set $\mathcal{S}$ and 0 otherwise. An alternative (and easier to code) version of matrix $\widehat{\mathbf{B}}$ is:

$$\widehat{\mathbf{B}} = \mathbf{Z}^{\top}(\widehat{\eta}\widehat{\eta}^{\top} \circ \mathbf{S})\mathbf{Z},$$

where the $IT \times IT$ selection matrix $\mathbf{S}$ has an entry (h, j) equal to one if the random terms η_h and η_j are correlated, and zero otherwise. In our case, only about 8% of the elements of $\mathbf{S}$ are nonzero. The Hadamard (term by term) multiplication is denoted by $\circ$. One difficulty comes from the fact that $\widehat{\mathbf{B}}$ is not necessarily positive definite. The same applies to our estimated parameters' variance matrix:

$$V[\widehat{\alpha}] = (\mathbf{X}^{\top}\mathbf{Z}\widehat{\mathbf{B}}^{-1}\mathbf{Z}^{\top}\mathbf{X})^{-1},$$

where the matrices $\mathbf{X}$ and $\mathbf{Z}$ are respectively of dimension $(IT \times K)$ and $(IT \times J)$ with the number of instruments not smaller than the number of regressors $L \geq K$. We follow Cameron et al. (2011) and impose positive definiteness on the parameters variance matrix by setting negative eigenvalues to zero in the eigendecomposition.[11]

Table 4.4 reports the estimated values of the parameters along with their standard deviations. The estimates of the fixed-effects and first difference specifications of the output demands are given for the purpose of comparison in columns 1 and 2. Our preferred specification relies on GMM and the corresponding estimated parameter values are included in the range of the fixed effects (FE) and the first difference (FD) estimates. The test for overidentification does not reject the validity of our instruments. According to the results obtained by GMM, the estimated short-run elasticity of demand with respect to price is -0.64 and is statistically significant at the 1% threshold. Domestic products and imports are substitutable with a cross price elasticity of 0.49. The coefficient of lagged output is estimated at 0.76 and found to be significant. This introduces a gap between short- and long-run price elasticities. The clustered standard errors are substantially smaller than the HAC-robust standard errors, probably because additional independence over spaced time periods is assumed when clustering.

[11]We actually compare different methods for imposing positive definiteness, by either restricting matrix $\mathbf{S}$, $\mathbf{B}$, $\widehat{\eta}\widehat{\eta}^{\top} \circ \mathbf{S}$ or $V[\widehat{\alpha}]$ to be positive definite, the results were different but in all cases, the diagonal terms of the restricted variance matrix were much lower than the HAC variance matrix.

Table 4.4: Output demand estimates

	FE	FD	FD-GMM
α_Y	0.92 (0.02)	0.05 (0.05)	0.76 (0.06), [0.03]
α_P	-0.12 (0.07)	-0.67 (0.17)	-0.64 (0.18), [0.08]
α_{IM}	0.04 (0.07)	0.55 (0.16)	0.49 (0.18), [0.07]
OIT	-	-	0.99

Notes: HAC robust standard errors are given in parenthesis, clustered standard errors are in brackets. OIT: p-value of the over-identification test, for the validity of the 130 orthogonality conditions.

These estimates are useful to calculate the inverse demand elasticity which is central in our model, and also for computing the long-run elasticities, characterized by $Y_{i,t-1} = Y_{it}$. These corresponding estimates are provided in Table 4.5. The inverse demand elasticity is obtained by $\varepsilon\left(P^d, Y\right) = 1/\varepsilon\left(Y^d, p\right)$ and is estimated to -1.56 in the short-run and -0.37 in the long-run. Standard errors are obtained using the delta-method (with the HAC variance matrix).

Table 4.5: Industry short- and long-run elasticities of output demand

	Short-run		Long-run	
	$\varepsilon\left(Y^d, p\right)$	$\varepsilon\left(P^d, Y\right)$	$\varepsilon\left(Y^d, p\right)$	$\varepsilon\left(P^d, Y\right)$
Estimate	-0.64	-1.56	-2.67	-0.37
s.e.	0.18	0.44	0.87	0.12

The short-run inverse price elasticity is substantial. With Cournot competition, there is an interesting relationship between the markup and the market share y/Y, parameterized by the inverse demand elasticity:

$$\frac{p}{\partial c/\partial y(w,y)} = \frac{1}{1+\varepsilon\left(P^d, Y\right) y/Y}. \tag{4.26}$$

Using the estimates of Table 4.5, we draw the estimated short- and long-run relationship between markup and market-share on Figure 4.2. Firms in the competitive fringe have a markup of 1. In conformity with point (iv) of Proposition 1, for which Figure 4.2 provides an illustration, the markup is monotonically increasing in market share. While in the short-run there is substantial markup for a firm having a market share of 20 to 30%, in the long-run this markup falls to the interval 1.08 - 1.12, which is quite small. However, in the short-run, sluggish adjustment toward market equilibrium price and quantity, according to the dynamic relationship (4.23) with strong anchoring to the lagged aggregate output level, confers substantial market power and a markup of 1.45 - 1.88 to the few firms with the biggest market share.

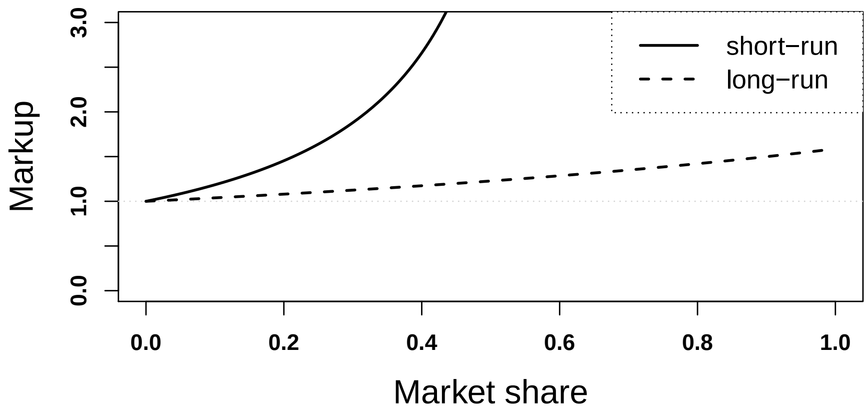

Figure 4.2: The markup and firms' market share

4.7 Cost function estimation with heterogeneity in fixed and variable costs

4.7.1 Empirical specification

It is well known that unobserved heterogeneity causes estimation biases when it is neglected while it is correlated with the explanatory variables, see for instance Gouriéroux and Peaucelle (1990) or Wooldridge (2010) for a detailed overview of the linear model. Unobserved heterogeneity also rises concerns about the incidental parameters, precluding consistent estimation of parameters and statistics of interest. Martin (2017) and Wooldridge (2019) consider unobserved multiplicative heterogeneity. When additive and multiplicative unobserved heterogeneity appears in the econometric specification, as is the case with our cost function, some specificities have to be considered. Then, the statistics of interest can be consistently estimated under reasonable assumptions. Let us now introduce the variable t for indicating the time dimension of the data. Given the quite long time dimension of our data, we now include a deterministic time trend, t, as a further argument of the cost function.

The first type of unobserved heterogeneity is specific to the production technologies and the cost functions characterizing a given industry. We deal with this difficulty, by estimating the cost specifications over all firms belonging to a given 2-digit industry (there are 19 different 2-digit manufacturing industries). Within a given industry, a further type of unobserved heterogeneity in the fixed and variable costs characterizes firms, and introduces correlation between their production and the random term. We propose a method for dealing with this endogeneity problem and avoiding estimation bias. As heterogeneity is unobserved it is subsumed in the additive random term and the cost function satisfies:

$$c_{nt} = u(w_{nt}, t) + v(w_{nt}, t, y_{nt}) + \epsilon_{nt} \tag{4.27}$$

$$\epsilon_{nt} \equiv u_{nt}(w_{nt}, t) - u(w_{nt}, t) + v_{nt}(w_{nt}, t, y_{nt}) - v(w_{nt}, t, y_{nt}) + \eta^c_{nt}. \tag{4.28}$$

We assume that the random term η^c_{nt} is such that $E[\eta^c_{nt}|w_{nt}, t, y_{nt}] = 0$. Its variance can exhibit heteroscedasticity and correlation. We use the reparameterization $u_{nt}(w_{nt}, t) = \gamma^u_{nt} u(w_{nt}, t)$ and $v_{nt}(w_{nt}, t, y_{nt}) = \gamma^v_{nt} v(w_{nt}, t, y_{nt})$. It can be written for any function u, which shows that these functions cannot be uniquely identified without imposing further conditions on the random term ϵ_{nt} or equivalently on the cost parameters $\gamma^u_{nt}, \gamma^v_{nt}$. For the sake of identification, we impose

$$E[\gamma^u_{nt}] = 1, \quad E[\gamma^v_{nt}] = 1. \tag{4.29}$$

Cost heterogeneity is known by the firm, but unobserved by the econometrician. If we were able to control for unobservable heterogeneity, the condition $E[\epsilon_{nt}|w_{nt}, t, y_{nt}, \gamma_{nt}] = 0$ would be useful for parameter estimation. However, $E[\epsilon_{nt}|w_{nt}, t, y_{nt}] \neq 0$ due to the fact that ϵ_{nt} includes the unobserved heterogeneity term γ^v_{nt} of the variable cost function and the optimal optimal production level is decreasing in γ^v_{nt} by (4.14). So $E[\epsilon_{nt} y_{nt}] \neq 0$ in (4.27) in general. Moreover, a firm can choose a high level of fixed cost if it allows to decrease its variable cost for (indirectly) achieving a higher production; in this case $E[\epsilon_{nt} y_{nt}] \leq 0$. We are interested in identifying the cost functions u and v which are common to all firms and time periods as well as the deforming weights $(\gamma^u_{nt}, \gamma^v_{nt})$. As there are twice more γ_{nt} parameter than observations, we will not be able to estimate them consistently, but we will be able to approximate their joint and marginal distributions, respectively denoted by $f_{uv}(\gamma^u, \gamma^v)$, $f_u(\gamma^u)$ and $f_v(\gamma^v)$. The firm and time specific heterogeneity is interesting in order to account for technological differences between firms and over time.

We specify the parametric forms for u and v. We consider that u and v belong to the family of quadratic cost functions:

$$\begin{aligned} u\left(w, t; \theta^u\right) &= \theta_w^\top w + \theta_{wt}^\top wt + \frac{1}{2}\frac{w^\top \Theta_{ww} w}{\zeta^\top w}, && (4.30)\\ v_1\left(w, t; \theta_1\right) y &= \left(\theta_{1w}^\top w + \theta_{1t}^\top wt + \frac{1}{2}\frac{w^\top \Theta_{1ww} w}{\zeta^\top w}\right) y, && (4.31)\\ v_2\left(w; \theta_2\right) y^2 &= \left(\theta_{2w}^\top w\right) y^2. && (4.32)\end{aligned}$$

The vectors of parameters θ_w, θ_{wt}, θ_{1w}, θ_{1t} and θ_{2w} have dimension $(J \times 1)$, whereas the symmetric matrices Θ_{ww} and Θ_{1ww} are $(J \times J)$. In order to identify the terms in the linear and quadratic fonctions of w, we impose that

$$\Theta_{ww} = \Theta_{ww}^\top, \quad \Theta_{1ww} = \Theta_{1ww}^\top, \tag{4.33}$$

$$\iota^\top \Theta_{ww} = \iota^\top \Theta_{1ww} = 0 \tag{4.34}$$

where ι denotes a $(J \times 1)$ vector of ones. We use the a Laspeyres price index $\zeta^\top w$ for total cost in order to impose linear homogeneity in w on the cost function. Both fixed and variable cost functions are flexible, in the sense that they provide a second order approximation to an arbitrary fixed and variable cost function; see Chen and Koebel (2017) on this point. There is a total of $5J + J(J-1)$ free parameters. In our case, $J = 3$ and there are 21 free parameters in the cost function.

4.7.2 Identification

Let us rewrite the cost function with unobserved heterogeneity:

$$c_{nt} = \gamma_{nt}^u u(w_{nt}, t; \theta^u) + \gamma_{nt}^v v(w_{nt}, t, y_{nt}; \theta^v) + \eta_{nt}^c \tag{4.35}$$

where $\theta^v = (\theta_1^\top, \theta_2^\top)^\top$. Let $w_n \equiv \{w_{ns}\}_{s \in \mathcal{T}_n}$, $y_n \equiv \{y_{ns}\}_{s \in \mathcal{T}_n}$ and $\mathcal{T}_n$ represents the set of all time indices for which firm n is observed. We assume that the additive random term satisfies strict exogeneity:

$$E[\eta_{nt}^c | w_n, t, y_n, \gamma_{nt}] = 0. \tag{4.36}$$

When cost heterogeneity is known by the firm, but unobserved by the econometrician, the firm knows $\gamma_{nt}^u, \gamma_{nt}^v$ when deciding about its output level, which is set to equalize marginal revenue and marginal cost:

$$p_t \left(1 + \varepsilon \frac{y_{nt}}{Y_t}\right) = \gamma_{nt}^v \frac{\partial v}{\partial y}(w_{nt}, t, y_{nt}; \theta^v) + \eta_{nt}^p$$

with the random term η_{nt}^p such that

$$E[\eta_{nt}^p | w_n, t, y_n, \gamma_{nt}^v] = 0. \tag{4.37}$$

Although fixed and variable costs are unobserved, it is helpful to split $\eta_{nt}^c = \eta_{nt}^u + \eta_{nt}^v$, and to consider explicitly both components in the total cost:

$$c_{nt} = \gamma_{nt}^u u(w_{nt}, t; \theta^u) + \eta_{nt}^u + \gamma_{nt}^v v(w_{nt}, t, y_{nt}; \theta^v) + \eta_{nt}^v.$$

We now define the fixed and variable cost functions as the conditional means:

$$\gamma_{nt}^{u} u(w_{nt}, t; \theta^{u}) = E[\gamma_{nt}^{u} u(w_{nt}, t; \theta^{u}) + \eta_{nt}^{u} | w_{n}, t, y_{n}, \gamma_{nt}^{u}] \tag{4.38}$$

$$\gamma_{nt}^{v} v(w_{nt}, t, y_{nt}; \theta^{v}) = E[\gamma_{nt}^{v} v(w_{nt}, t, y_{nt}; \theta^{v}) + \eta_{nt}^{v} | w_{n}, t, y_{n}, \gamma_{nt}^{v}]. \tag{4.39}$$

This imposes two strict exogeneity conditions on the idiosyncratic random terms η_{nt}^{u} and η_{nt}^{v}, which are inherited by η_{nt}^{c}. These requirements allow us to interpret the functions u, v as the fixed and variable cost function of a representative firm, defined by $\gamma_{nt}^{u} = \gamma_{nt}^{v} = 1$. The main difficulty we are confronted with in this section, is that $\gamma_{nt}^{u}, \gamma_{nt}^{v}$ are unobserved and potentially correlated with w_{nt}, y_{nt}, and in our empirical part, we cannot control for it as we do in (4.36) - (4.39). This prevents consistent estimation of the parameters of interest when simply ignoring unobserved heterogeneity.

We try to capture unobserved heterogeneity, and follow a proxy variable approach similar to Olley and Pakes (1996) and Levinsohn and Petrin (2003) in the context of production functions. For this purpose, we rely on plausible assumptions to identify the values taken by these functions. We begin to note that the relative values u_{nt}/u and v_{nt}/v denote the relative state of firm n's technology at time t in comparison to a reference technology denoted by u that is identical for all firms and time periods. These relative efficiency levels may depend upon input prices and the production level, on unobserved firm specific effects, time specific affect, lagged efficiency level achieved at $t-1$ (a Markovian process further discussed below), and, as these relative efficiency levels are known to the firm, it will invest more intensively when both efficiency indicators are good. Like Olley and Pakes (1996) we also consider the age of the firm, and as recommended by Wooldridge (2019) we consider the number of firms' occurrences in the data, to capture selection effects.[12] Let us gather all these variables into the vector z_{nt}, and consider the following version of a (conditional) strict exogeneity assumption:

Assumption 8. Conditionally to z_{nt} the random terms satisfy:

$$E[\eta_{nt}^{c} | w_{n}, t, y_{n}, z_{nt}] = 0, \tag{4.40}$$

$$E[\eta_{nt}^{p} | w_{n}, t, y_{n}, z_{nt}] = 0, \tag{4.41}$$

$$E[\gamma_{nt}^{u} | w_{n}, t, y_{n}, z_{nt}] = \gamma^{u}(z_{nt}), \tag{4.42}$$

$$E\left[\gamma_{nt}^{v} | w_{n}, t, y_{n}, z_{nt}\right] = \gamma^{v}(z_{nt}). \tag{4.43}$$

The first two conditions of Assumption 8 (A8) correspond to strict exogeneity of the additive random terms conditionally to z_{nt}. In order to highlight the scope of A8 (4.40) and

[12] See Appendix 4.10, Table 4.13, for some descriptive statistics for these variables.

(4.41), we compare these conditions with $E[\eta^c_{nt}|w_n, y_n, \gamma_{nt}] = 0$ that was used earlier, but which is not useful when the γ_{nt} are unknown. If the instruments z_{nt} are sufficiently comprehensive, then the conditions in A8 (4.40) provides a good proxy for $E[\eta^c_{nt}|w_n, t, y_n, \gamma_{nt}] = 0$ and is informative about the data generating process. Regarding the multiplicative random terms, γ^u_{nt} and γ^v_{nt}, the requirements in A8 given by (4.42) and (4.43) are less restrictive than it may appear at first sight: it does not exclude the case where w_{nt}, y_{nt} are arguments of γ^u, γ^v, this is achieved with the instruments $z_{nt} = (w_{nt}, y_{nt})^\top$. A8 also encompasses the first order Markov process usually considered in the productivity and industrial organization literature. For instance, if we assume that z_{nt} includes current production and lagged unobserved heterogeneity, $z_{nt} = (y_{nt}, \gamma_{n,t-1})^\top$, then A8 (4.43) states that:

$$E\left[\gamma^v_{nt}|w_n, y_n, z_{nt}\right] = \gamma^v(y_{nt}, \gamma_{n,t-1}),$$

which in turn implies that (after integrating out y_{nt}):

$$E\left[\gamma^v_{nt}|\gamma_{n,t-1}\right] = f^v(\gamma_{n,t-1}), \tag{4.44}$$

just like in Olley and Pakes (1996), Ackerberg et al. (2015) or Wooldridge (2009). The flexibility of the statement in A8 allows us to nest different models and to test the validity of different specifications or sets of instruments.

The vector z_{nt} includes variables which are correlated with unobserved heterogeneity and uncorrelated with the random terms $\eta_{nt} = (\eta^c_{nt}, \eta^p_{nt})^\top$. Applying A8 to our parametric model, implies that:

$$E[c_{nt}|w_n, t, y_n, z_{nt}] = \gamma^u(z_{nt})u(w_{nt}, t; \theta^u) + \gamma^v(z_{nt})v(w_{nt}, t, y_{nt}; \theta^v), \tag{4.45}$$

$$E\left[p\left(1 + \epsilon\frac{y_{nt}}{Y_t}\right)|w_n, t, y_n, z_{nt}\right] = \gamma^v(z_{nt})\frac{\partial v}{\partial y}(w_{nt}, t, y_{nt}; \theta^v). \tag{4.46}$$

Several estimation strategies can be followed. With Cobb-Douglas type production functions, a semi-parametric two-stage approach is often adopted (see Ackerberg et al. (2015) for references). The first stage consists in a nonparametric estimation of the technology. In a second stage, the parameters of interest are identified. In contrast, we rely on a full (but quite flexible) parametric specification. In our context, many variables are included in z_{nt} and the curse of dimensionality prevents us from using a nonparametric setup. Another advantage of a parametric specification, is that it is computationally less burdensome in face of a large number of observations. We can also quite easily estimate the system of equations while imposing cross equations identifying restrictions. These advantages may outweight issues related to misspecifications of the functional form for γ. The third advantage of a parametric specification is that it allows for correlated random γ terms when including, as advocated by Wooldridge (2019), firm (and time) specific means into z_{nt}. The last advantage of our parametric approach, and also highlighted by Wooldridge (2009), is that a single estimation step is sufficient to provide most statistics of interest.

For simplicity, we specify the γ^j in A8 as linear functions in the parameters and in the explanatory variables for $j = u, v$:

$$E[\gamma^j_{nt}|w_n, y_n, z_{nt}] = 1 + (z_{nt} - \bar{z})^\top \beta^j, \tag{4.47}$$

where the constant vector of empirical means $\bar{z}$ is substracted to ensure that the unconditional expectations satisfy $E[\gamma^j_{nt}] = 1$.

In order to impose the dynamic relationship (4.44) on the unobserved heterogeneity terms, Wooldridge (2009) proposes appending the following conditional expectations to the system to be estimated:

$$E[c_{nt}|w_n, t, y_n, z_{n,t-1}] = f^u(\gamma_{n,t-1})u(w_{nt}, t; \theta^u) + f^v(\gamma_{n,t-1})v(w_{nt}, t, y_{nt}; \theta^v), \tag{4.48}$$

$$E\left[p\left(1 + \epsilon\frac{y_{nt}}{Y_t}\right)|w_n, t, y_n, z_{n,t-1}\right] = f^v(\gamma_{n,t-1})\frac{\partial v}{\partial y}(w_{nt}, t, y_{nt}; \theta^v), \tag{4.49}$$

with

$$\gamma_{n,t-1} = 1 + (z_{n,t-1} - \bar{z})^\top \beta^j + \varepsilon^j_{nt}.$$

The nonparametric literature identifies the structural model parameters θ and the unobserved productivity estimates for γ^j in a second step, by imposing further modeling restrictions and orthogonality conditions on the model.[13]

After inclusion of the linear specifications for γ^j into the expected value of the cost function, and marginal revenue function (4.45), (4.46), we obtain a large polynomial in $(w_{nt}, t, y_{nt}, z_{nt})$ nonlinear in structural parameters (θ, β). In order to estimate the models' parameters, we reparameterize the model to obtain a more general specification, encompassing the structural nonlinear model, and which is linear in newly defined parameters, which are now denoted by $\boldsymbol{\alpha}$ and are related to the structural parameters by the nonlinear relationship:

$$\boldsymbol{\alpha} = g(\theta, \beta), \tag{4.50}$$

with $\theta \equiv (\theta^{u\top}, \theta^{v\top})^\top$, $\beta \equiv (\beta^{u\top}, \beta^{v\top})^\top$. The function $g : \mathbb{R}^K \to \mathbb{R}^L$ defines, in our case, more identifying restrictions than structural parameters: $L \geq K$. Doing so, we are able to rewrite our model as: $\boldsymbol{Y} = \boldsymbol{X}\boldsymbol{\alpha} + \boldsymbol{\varepsilon}$, which is quite convenient for estimation as we can rely on (pooled) OLS to estimate $\boldsymbol{\alpha}$ and to identify all parameters of the structural model.[14]

[13] Whether parametric or nonparametric, both approaches take for granted that $\varepsilon^j_{nt} = 0$ or equivalently that $\gamma^v_{nt} = f^v(\gamma_{n,t-1})$ without error, and that unobserved shocks follow a Markov process. Interestingly, we achieve identification of the structural parameter (and statistics of interest) without imposing these restrictions.

[14] See Appendix 4.11 for more details on the reparameterization of the model.

Proposition 6. Under the identification assumption (4.29), A8, and full column rank of $\boldsymbol{X}$, the parameters θ, and β of the structural model (4.45), (4.46) are identified.

See Appendix 4.9 for a proof. In practice, we identify the predicted unobserved heterogeneity terms a follow. We use the predicted values of the marginal revenue regression and divide it with the predicted value of the marginal cost (obtained from the cost regression) :

$$\widehat{\gamma}^v_{nt} = \frac{\widehat{\gamma^v \partial c/\partial y}}{\widehat{\partial c/\partial y}}. \tag{4.51}$$

We then use the values of $\widehat{\gamma}^v_{nt}$ together with predicted total cost to identify the predicted fixed cost heterogeneity as

$$\widehat{\gamma}^u_{nt}\widehat{u}_{nt} = \widehat{c}_{nt} - \widehat{\gamma}^v_{nt}\widehat{v}_{nt} \implies \widehat{\gamma}^u_{nt} = \frac{\widehat{c}_{nt} - \widehat{\gamma}^v_{nt}\widehat{v}_{nt}}{\widehat{u}_{nt}}. \tag{4.52}$$

The following table summarizes several specifications for γ^j that were estimated. The baseline Model 1 (for which $\gamma^u = \gamma^v = 1$) is the most restrictive. In each row we add new explanatory variables in the specifications of both γ^j as indicated in the columns of Table 4.6. When comparing the nested models 1 to 4 by using a Fisher test (based on the comparison of residuals sum of squares), we reject the validity of the more restrictive specifications against the more general on given by Model 4.

Table 4.6: List of included variables in γ^u and γ^v

	$\ln w_{l,nt}$	$\ln y_{nt}$	$\overline{\ln w}_{l,n}$	$\overline{\ln y}_n$	T_n	i_{nt}	a_{nt}	# of parameters	Fisher test (p-value)
Model 1								21	
Model 2	✓	✓	✓	✓	✓			21+75	0.00
Model 3	✓	✓	✓	✓	✓	✓		21+90	0.00
Model 4	✓	✓	✓	✓	✓	✓	✓	21+105	0.00

Note: Individual means of firms' labor prices and production are given by $\overline{\ln w}_{l,n} = T_n^{-1}\sum_{t=1}^{T_n} \ln w_{l,nt}$, and similarly for $\overline{\ln y}_n$, where T_n denotes the number of observations of a specific firm. i_{nt} and a_{nt} denote firms' investments and age, respectively.

4.7.3 Estimation results

Returns to scale and rate of technological change

This subsection evaluates the rate of Returns to Scale (RTS) defined by

$$\frac{\partial \ln c}{\partial \ln y}(w, t, y), \tag{4.53}$$

over our observations. When the estimated statistic is lower than one, the observation exhibits increasing RTS, while RTS are constant or decreasing when the statistic is equal to or greater than one. The cost function also comprises a time trend as argument, and allows us to compute estimates for the Rate of Technological Change (RTC):

$$\frac{\partial \ln c}{\partial t}(w, t, y). \tag{4.54}$$

These statistics depend upon the explanatory variables (both observed and unobserved) and are different for each observation in our sample.

Table 4.7 summarizes the elasticity of total cost with respect to output, which corresponds to our measure of the rate of return to scale. While the estimated values depend somewhat on the model specification, the broad conclusions are the same over all models: there is evidence for a variety of rate of returns: about 40% of the observations exhibit increasing returns to scale, 25% have almost constant returns to scale, while about 35 % of the observations have decreasing RTS. Our baseline Model 1 (without correlated unobserved heterogeneity) is already compatible with some heterogeneity in RTS over observations, and the distribution of the rates of RTS are broadly compatible with those obtained for the more general Models 2 to 4.

Table 4.7: Distribution of firms' returns to scale

	Model 1	Model 2	Model 3	Model 4
P25	0.89	0.86	0.83	0.83
P50	1.04	1.01	0.98	0.98
P75	1.16	1.11	1.09	1.09
MAD	0.13	0.12	0.12	0.12

Note: P25, P50, and P75 report the 25^{th}, the 50^{th}, and the 75^{th} percentile of the respective distribution. MAD denotes the Median Absolute Deviation.

Estimates for increasing returns are quite common for cost functions, and this result contrasts with the estimates usually found with a production function approach which often make a case for decreasing returns to scale. See for instance Diewert and Fox (2008) for a discussion. These contradictory empirical results are often attributed to the endogeneity of the production level in the cost function, which is expected to be correlated with unobserved heterogeneity. As our approach controls for unobserved heterogeneity, we expect no endogeneity bias to occur in our estimates. The finding that increasing RTS do not disappear in Model 4, despite the strong statistical rejection of Model 1 (see Table 4.6), supports the hypothesis according to which increasing RTS are not due to endogeneity of output.

The quartiles of the estimates for the RTC are given in Table 4.8. The median value of the RTC is negative, and indicates that for given values of (w, y), costs tend to decrease over time, by a median value of 0.71% (Model 1) or 0.24% (Model 4). This measure of technological change, however, varies quite importantly over the 4 specifications considered. This quite important difference between Model 1, neglecting unobserved heterogeneity, and Model 4, which is the most flexible specification, is not surprising. Indeed, Model 2-4 allow for correlated technological progress (mediated through changes in γ^u, γ^v), while Model 1 only considers the deterministic and exogenous time trend as source of technological change. Overall, we conclude that about 50% of technological change is endogeneous and reallocates output over firms.

Table 4.8: Distribution of firms' rate of technological change

	Model 1	Model 2	Model 3	Model 4
P25	-3.29	-1.81	-1.36	-1.77
P50	-0.71	-0.01	-0.08	-0.24
P75	0.67	1.49	0.77	0.89
MAD	1.80	1.66	1.06	1.33

Note: P25, P50, and P75 report the 25^{th}, the 50^{th}, and the 75^{th} percentile of the respective distribution. MAD denotes the Median Absolute Deviation.

For about 40% of the estimated total cost tend to increase over time, this means that many firms have to compensate this positive trend by lower values of (γ^u, γ^v) if they want to keep their cost efficiency unchanged or improved.

Unobserved heterogeneity

We first provide some insights in the distribution of estimated values of the unobserved fixed and variable cost efficiency, $\widehat{\gamma}^u_{nt}$ and $\widehat{\gamma}^v_{nt}$. Table 4.9 presents the quartiles of their respective distribution and allows comparing different specifications of unobserved heterogeneity. As already discussed, Model 1 does not take any unobserved heterogeneity into account, which is equivalent to $\widehat{\gamma}^u_{nt} = \widehat{\gamma}^v_{nt} = 1$, for all n, t. Comparing the other models, we find a wide degree of unobserved heterogeneity especially in firms' fixed cost parameter. Considering Panel A, it can be seen that distribution of $\widehat{\gamma}^u_{nt}$ changes somewhat by increasing the number of z-variables contained the function of $\widehat{\gamma}^u$ and $\widehat{\gamma}^v$. Instead, Panel B shows that the distribution of $\widehat{\gamma}^v$ is much more stable over the different models, and highly concentrated around one, which is also indicated by the small MAD.

Table 4.9: Distribution of $\widehat{\gamma}^u_{nt}$ and $\widehat{\gamma}^v_{nt}$

	Model 1	Model 2	Model 3	Model 4
Panel A: Distribution of $\widehat{\gamma}^u$				
P25	1.00	-0.33	-0.31	-0.33
P50	1.00	0.31	0.30	0.26
P75	1.00	1.20	1.07	1.06
MAD	0.00	0.75	0.68	0.68
Panel B: Distribution of $\widehat{\gamma}^v$				
	Model 1	Model 2	Model 3	Model 4
P25	1.00	0.94	0.90	0.90
P50	1.00	0.98	0.99	0.99
P75	1.00	1.01	1.08	1.07
MAD	0.00	0.04	0.09	0.09

Note: P25, P50, and P75 report the 25^{th}, the 50^{th}, and the 75^{th} percentile of the respective distribution. MAD denotes the Median Absolute Deviation.

The parameters respectively represent fixed and variable cost unobserved heterogeneity, so that we can conclude from these figures that about 60% of all firms operate with virtually zero or very small fixed cost. The other firms have a positive fixed cost, and there is considerable heterogeneity about the size of these fixed cost. The parameter γ^v represents variable cost heterogeneity. We conclude from panel B, that while about 25% of the firms have a variable cost of 10% below average (for which $\gamma^v = 1$), there are also 25% of the firms with average costs higher than average by 7% or more. This unobserved heterogeneity is economically relevant, and strongly influences firms' size, according to Proposition 3.

As the Fisher test (Table 4.6) supports the specification of Model 4, we report below only results based on that model. For instance, Figure 4.3 shows kernel density estimates of the distribution of $\widehat{\gamma}^u$ (on the left) and $\widehat{\gamma}^v$ (on the right).[15] Both densities are single peaked, and show that there is a high probability mass around $\gamma^u = 0$ and around $\gamma^v = 1$. For completeness, we also report on Figure 4.5 and 4.4 the joint density of $\widehat{\gamma}^u$ and $\widehat{\gamma}^v$ as well as the corresponding contour plot. From this figure, there is a priori no strong dependence between both random variables, and the existence of a relationship like (4.11) is not supported by our estimates.

[15] The densities are estimated using a second-order Gaussian kernel and likelihood cross-validation to obtain optimal bandwidths.

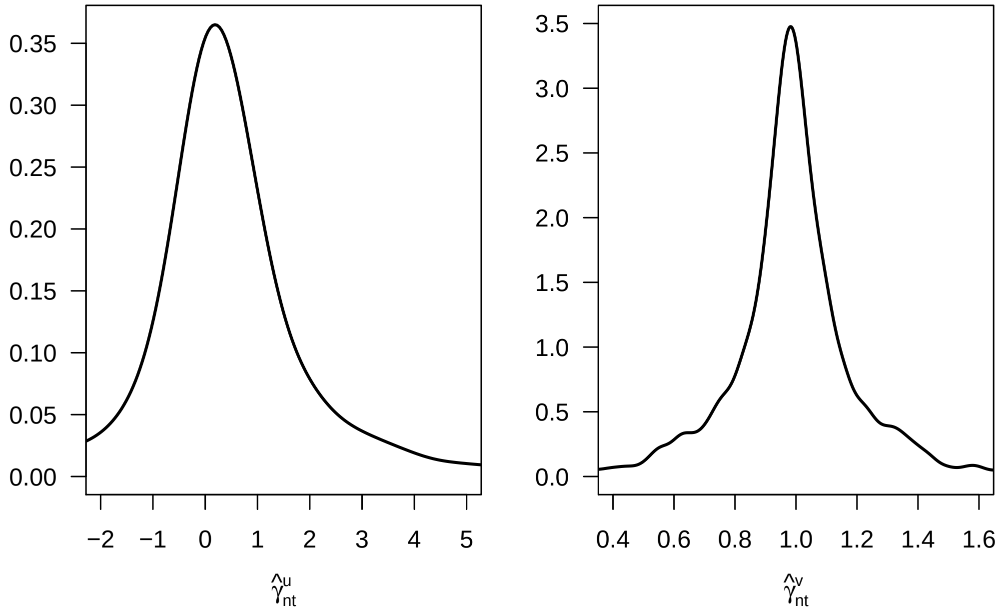

Figure 4.3: Kernel density estimate of unobserved fixed and variable cost parameters, $f_u(\widehat{\gamma}^u)$ and $f_v(\widehat{\gamma}^v)$

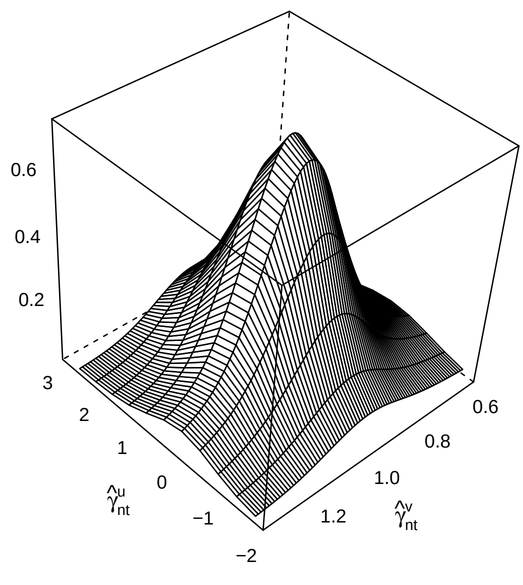

Figure 4.4: Joint density estimate of unobserved cost parameters $f(\widehat{\gamma}^u, \widehat{\gamma}^v)$

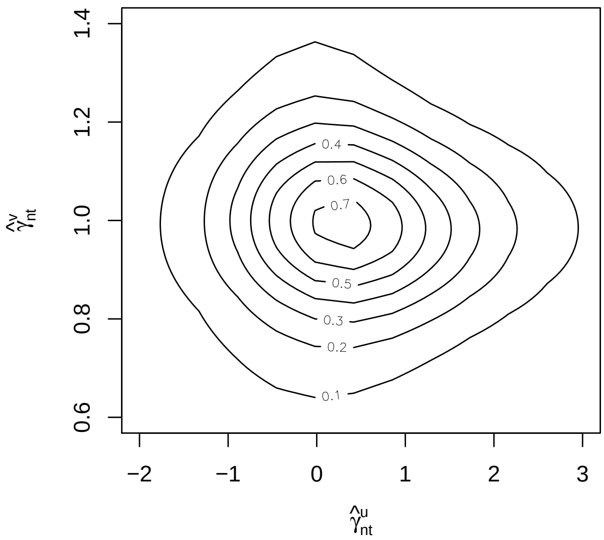

Figure 4.5: Contour plot of the joint density of unobserved cost parameters $f(\widehat{\gamma}^u, \widehat{\gamma}^v)$

Heterogeneity by firm size and years

One of the main conclusion of the Cournot model is that there is an ordering of unobserved heterogeneity and firm size. We investigate these relationship further and report the above statistics by firm size. Table 4.10 completes the information given in Tables 4.7 and 4.8 and reports, among other, the median value of fixed and variable cost, together with RTS and RTC over firm size. Surprisingly, we find that the fixed costs represent 80% of total cost for firms with one employee, and this falls to 23% for firms with 2 to 4 employees. This value is below 5% for most sizes, but suddenly increases to 8 % for the biggest firms with 500 employees and more. The median value is γ^u is globally increasing with firm size, while the median of γ^v is almost constant, close to 1, but falls to 0.88 for the biggest firms in our sample. This means that these firms are more efficient than average, in conformity with Proposition 3(i). These findings also highlight the shortcomings of usual specifications for cost functions, as the Cobb-Douglas or the translog, which exclude by construction the occurrence of fixed costs. Table 4.10 shows that increasing returns are mainly prevalent for big firms in the upper tail of the size distribution. Some small firms also exhibit increasing RTS, in relation with higher than average fixed costs, and the difficulty to achieve a positive profit. For all small and medium size classes the median RTS is close to 1 (constant RTS). For the largest firms, however, we find the strongest median RTS with a value of 0.91, which is related to their market power and conform to Proposition 1(iii). Regarding technological change, the estimated median value of $\partial \ln c / \partial t$ is almost monotonically decreasing with firm size. For the smallest firms, the RTC is very important and represents a cost reduction of

0.72% by year, ceteris paribus. This rate rapidly decreases with firm size (in absolute value), and is close to 0 for the largest firms. This empirical evidence strongly supports Arrow's view about the virtue of competition for innovation, against Schumpeter's argument. (We are aware though that cost reduction is only one aspect of innovation.)

Table 4.10: Median statistics by firm size[a,b]

Firm size	$\frac{\hat{\gamma}^u_{nt}\hat{u}}{c_{nt}}$	$\hat{\gamma}^u_{nt}$	$\hat{\gamma}^v_{nt}$	$\frac{\partial \ln c}{\partial \ln y}$	y_{nt}/Y_t	Markup	$\frac{\partial \ln c}{\partial t}$	$cor(c_{nt}, \hat{c}_{nt})$	$cor(mr_{nt}, \widehat{mc}_{nt})$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1	0.80	0.18	0.99	1.00	0.00	1.00	-0.72	0.77	0.52
2-4	0.23	0.17	0.98	0.97	0.01	1.00	-0.53	0.75	0.63
5-9	0.08	0.24	0.98	0.97	0.02	1.00	-0.34	0.86	0.68
10-19	0.04	0.31	0.98	0.98	0.04	1.00	-0.13	0.90	0.69
20-49	0.03	0.41	1.01	0.99	0.10	1.00	-0.06	0.98	0.71
50-99	0.02	0.62	1.02	0.98	0.26	1.00	-0.05	0.94	0.72
100-199	0.02	0.84	1.03	0.97	0.59	1.01	-0.04	0.92	0.66
200-499	0.03	1.25	1.02	0.95	1.35	1.02	-0.08	0.93	0.59
500+	0.08	2.30	0.88	0.91	4.82	1.08	0.03	1.00	0.33
Total	0.08	0.26	0.99	0.98	0.02	1.00	-0.24	1.00	0.63

[a] Firm sizes are measured by the number of employees.

[b] Column (1) reports the share of fixed costs over total costs, (4) reports returns to scale, (5) reports 4-digit market shares, (7) reports the rate of technological progress, (8) reports the correlation between firms' observed costs and the fitted values from the cost regression, and (9) reports the correlation between firms' (computed) marginal revenues and the fitted values of the marginal cost.

The last two columns of Table 4.10 give an indication of the fit obtained by our model, for both regressions and different firm sizes. While our cost function fits the cost data quite well for all size groups, the marginal cost function is farther away from the marginal revenue function, especially for the smallest and biggest firm sizes.

We also illustrate how some key estimates change over the entire sample period from 1994 to 2016. In particular, Figure 4.6 shows the evolution of the median of $\hat{\gamma}^u$, which fluctuates around 0.25 over the period. Instead, the evolution of the median value of $\hat{\gamma}^v$, depicted on Figure 4.6, reveals a clearly decreasing pattern in a quite narrow range, from about 1.04 in 1994 to 0.94 in 2016. This implies that, at the median, firms produce with a lower variable cost over time. The decrease is not continuous, however, and γ^v remains almost constant around 0.95 from 2008 onwards. Figure 4.8 depicts the evolution of returns to scale over time and illustrate that this value varies little over time and remains close to 1. Regarding technological change, Figure 4.9 reports the median value of the RTC, i.e. the change in costs w.r.t. time, for constant γ^u, γ^v. For most periods, we estimate a negative median RTC, indicating that firms generally become more cost efficient over time. However, we also see that the median RTC slows down from 2008 forward and stabilizes to a value around 0 in 2012 and after.

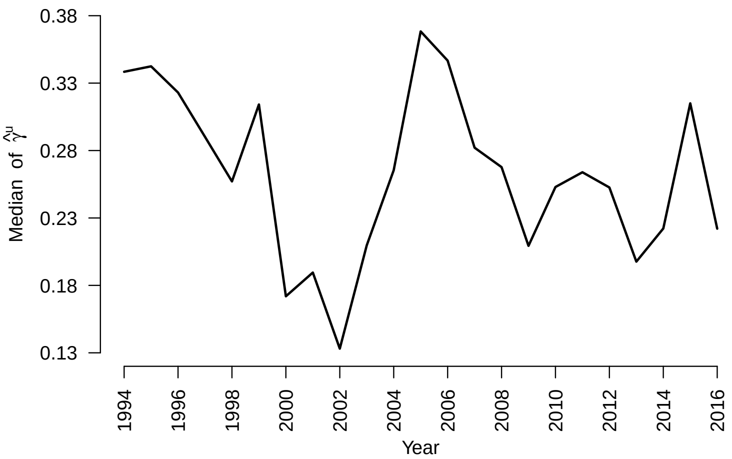

Figure 4.6: Median evolution of unobserved fixed cost efficiency $\widehat{\gamma}^u$

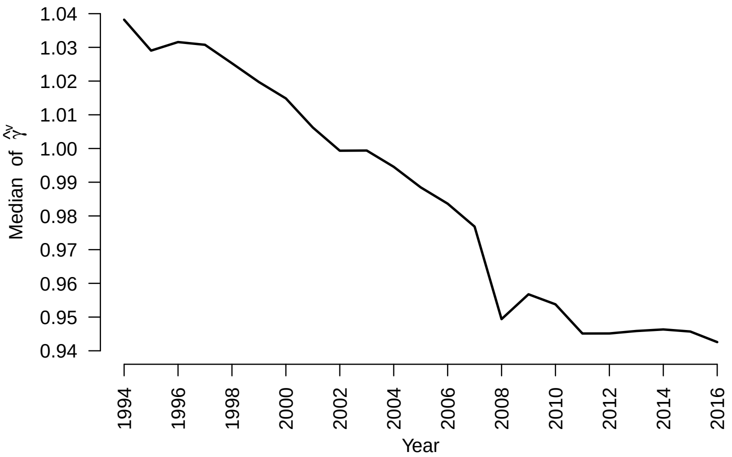

Figure 4.7: Median evolution of unobserved fixed cost efficiency $\widehat{\gamma}^v$

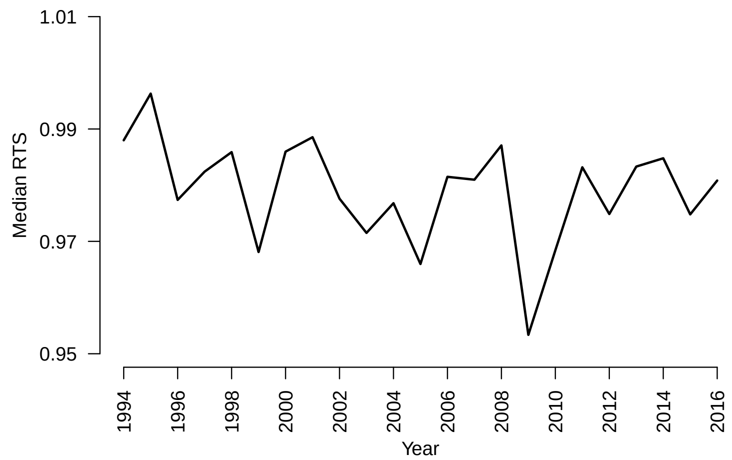

Figure 4.8: Median value of the rate of returns to scale over time

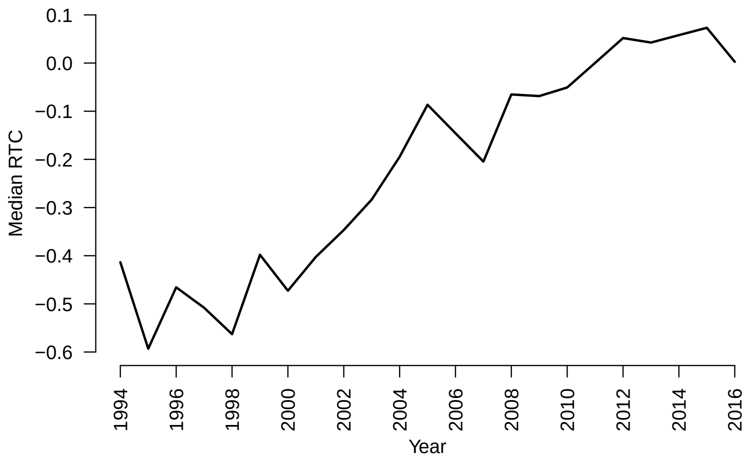

Figure 4.9: Median value of the rate of technological change over time

Firm size distribution

One of our objectives was to propose a theoretical and empirical model able to cope with unobserved heterogeneity and able to endogenously reproduce the distribution of output levels over firms. Econometric models neglecting unobserved heterogeneity fail in this respect. Additive unobserved heterogeneity in the cost function only will miss the point, because this type of heterogeneity disappears in the marginal cost function. Hence our specification with bivariate joint heterogeneity in fixed and variable (or marginal) cost. We now evaluate our econometric approach by comparing the actual distribution of firms' output levels with the one endogenously predicted by our model. We predict the optimal production level $\widehat{y}_{nt}^{C}$ for each firm (at Cournot equilibrium) using (4.14), and report the corresponding density on Figure 4.10. We also consider the Cournot model without unobserved heterogeneity (Model 1) and compute firms' optimal output level $\widehat{y}_{nt}^{C,sym}$ by (4.14) after setting $\gamma^u = \gamma^v = 1$. It is convenient to represent the density for the logarithm of the output level to avoid having a large support with paucity of observations when output is measured in level.

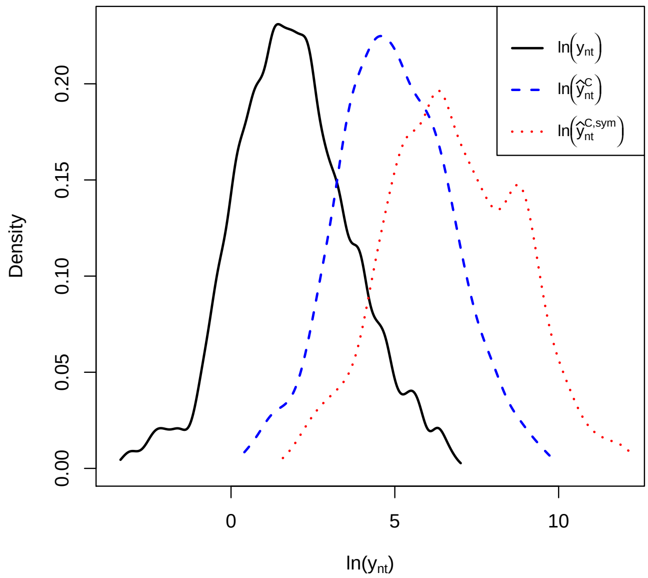

Figure 4.10: Firms' size distributions, observed and predicted

Figure 4.10 is informative both about the strengths and shortcomings of our approach. All three distributions have a similar shape but quite a different support. Our model including unobserved heterogeneity is closer to the observed log-output distribution than the model neglecting it (or considering it as random and uncorrelated with output). The three densities reach a peak at respectively $\ln y = 1$, $\ln y = 5$ and $\ln y = 7$, which represents a sizable gap between observed and predicted production values. The main reason for this discrepancy is that our model targets the cost and the marginal cost function, but not the production level of our firms. Our objective is to extend our model to include this additional criteria into the econometric framework, either by using a moment fitting or simulated maximum likelihood approach. A further reason for the lack of fit between the log-output distributions is that we have included only two unobserved heterogeneity terms, which respectively affect the fixed cost and the first derivative of the cost function. A third unobserved heterogeneity term is actually needed to allow for heterogeneous second order derivatives of the cost function w.r.t. y, and which determines the optimal (and heterogeneous) firm size. Such extensions are part of our future research agenda.

4.8 Conclusion

This chapter investigates Cournot competition and highlights the regularities emerging in this context between firm size, market shares, marginal cost and market power. While greater firm size is a good indicator of cost efficiency, it is at the same time an indicator of welfare inefficiency due to market power. Whereas most competition policies limit the overall inefficiency by constraining firms' admissible market shares, we emphasize that an alternative policy could be to promote firms' cost efficiency while limiting their market power.

Our empirical contribution consists in developing an estimation strategy that allows to identify the distribution of two multiplicative correlated random terms: one affecting the fixed cost and one associated with the variable cost of production. In this context, standard estimation procedures yield inconsistent estimates. We extended a technique available for the estimation of one additive productivity term occurring with a production function to two multiplicative terms affecting the cost function. The empirical results highlight the importance of both observed and unobserved heterogeneity for explaining firms' cost and marginal revenues. Fixed costs are often very small, but found to be significant for the smallest and largest firm sizes, which may have policy implications, both for increasing the survival probability of small firms, than for fighting inefficiencies (or market power) of bigger firms. Unobserved heterogeneity in variable costs give a competitive advantage to bigger firms by lowering their variable cost function (ceteris paribus). However, we also estimate that this type of cost efficiency is compensated by lack of technological improvement over time for bigger firms.

One important theoretical result is the generalization of Mankiw and Whinston (1986)'s theorem about excess entry at Cournot equilibrium to the case of heterogeneous firms. It would be interesting in a further study to evaluate quantitatively the size of the inefficiencies due to too many small firms producing with fixed cost and high variable cost, and to evaluate the welfare gains of redistributing their production to bigger firms producing with lower marginal cost. For this purpose, Proposition 4 would be helpful to characterize the different configurations, and guide us for writing the computer code for redistributing market shares. We could then compute the optimal degree of concentration together with the optimal number of firms active in each market. Before to be able to tackle this issue, however, we have to amend our model and estimation approach towards still more flexibility, so that our models' predictions still improve and catch more stylized facts of the industrial structure.

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4.9 Appendix A: Proof of the propositions

Proof of Proposition 1.

(i) and (ii). By A1 it follows that $\epsilon(P,Y) \equiv P'(Y)Y/P(Y) < 0$. By A2, at equilibrium $P(Y) + P'(Y)y_n^N > 0$ hence $P(Y)\left(1 + \epsilon(P,Y)y_n^N/Y\right) > 0$. Summing these inequalities over N gives (i). The inequality also implies that individual market shares are bounded above: $y_n^N/Y < -1/\epsilon(P,Y)$.

(iii) From the first order condition $\partial c_n/\partial y = P(Y)(1 + \epsilon(P,Y)y_n^N/Y)$ it turns out that at Cournot equilibrium

$$y_i^N > y_j^N \Leftrightarrow \frac{\partial c_i}{\partial y}\left(w_i, y_i^N\right) < \frac{\partial c_j}{\partial y}\left(w_j, y_j^N\right).$$

Claim (iv) directly follows from (iii) and the definition of the price markup $P/(\partial c_n/\partial y)$.
Claim (v) corresponds to Okumura (2015, Lemma 1). □

Proof of Proposition 2.

Input prices could be heterogeneous over firms, but without affecting the result, so we use notation w instead of w_n. The Cournot equilibrium is characterized by N individual production levels $y_n^N\left(w, \{\gamma_n^v\}_{n=1}^N\right)$ and $Y^N\left(w, \{\gamma_n^v\}_{n=1}^N\right)$ such that the first and second order optimality conditions are satisfied. We find it convenient to omit the arguments $\left(w, \{\gamma_n^v\}_{n=1}^N\right)$ of Y^N and y_n^N in the equations below. At Cournot equilibrium, individual and aggregate output levels satisfy:

$$\begin{aligned} P\left(Y^N\right) + P'\left(Y^N\right)y_i^N &= \gamma_i^v \frac{\partial v}{\partial y}\left(w, y_i^N\right) \\ Y^N &= \sum_{n=1}^{N} y_n^N \end{aligned}$$

Differentiating the first order optimality condition with respect to γ_i^v for two different firms, i and n, gives

$$\begin{aligned} \left(P'\left(Y^N\right) + P''\left(Y^N\right)y_i^N\right)\frac{\partial Y^N}{\partial \gamma_i^v} + P'\left(Y^N\right)\frac{\partial y_i^N}{\partial \gamma_i^v} &= \frac{\partial v}{\partial y}\left(w, y_i^N\right) + \gamma_i^v \frac{\partial v^2}{\partial y^2}(w, y_i)\frac{\partial y_i^N}{\partial \gamma_i^v} \\ \left(P'\left(Y^N\right) + P''\left(Y^N\right)y_n^N\right)\frac{\partial Y^N}{\partial \gamma_i^v} + P'\left(Y^N\right)\frac{\partial y_n^N}{\partial \gamma_i^v} &= \gamma_n^v \frac{\partial v^2}{\partial y^2}\left(w, y_n^N\right)\frac{\partial y_n^N}{\partial \gamma_i^v}. \end{aligned}$$

Let us define

$$a_n^N \equiv \left[P'\left(Y^N\right) - \gamma_n^v \frac{\partial v^2}{\partial y^2}\left(w, y_n^N\right)\right]^{-1},$$

which is negative by A3(ii), and write

$$\begin{aligned}
\frac{\partial y_i^N}{\partial \gamma_i^v} &= a_i^N \cdot \left(\frac{\partial v}{\partial y} \left(w, y_i^N \right) - \left(P' \left(Y^N \right) + P'' \left(Y^N \right) y_i^N \right) \frac{\partial Y^N}{\partial \gamma_i^v} \right) \\
\frac{\partial y_n^N}{\partial \gamma_i^v} &= -a_n^N \cdot \left(P' \left(Y^N \right) + P'' \left(Y^N \right) y_n^N \right) \frac{\partial Y^N}{\partial \gamma_i^v}
\end{aligned}$$

If we sum all partial effects $\partial y_n^N / \partial \gamma_i^v$ over all $n = 1$ to N this gives

$$\begin{aligned}
\frac{\partial Y^N}{\partial \gamma_i^v} &= -\sum_{n=1}^{N} a_n^N \cdot \left(\left(P' \left(Y^N \right) + P'' \left(Y^N \right) y_n^N \right) \frac{\partial Y^N}{\partial \gamma_i^v} \right) + a_i^N \frac{\partial v}{\partial y} \left(w, y_i^N \right) \\
\Rightarrow \quad & \frac{\partial Y^N}{\partial \gamma_i^v} = \frac{a_i^N}{1 + \sum_{n=1}^{N} \left(P' \left(Y^N \right) + P'' \left(Y^N \right) y_n^N \right) a_n^N} \frac{\partial v}{\partial y} \left(w, y_i^N \right).
\end{aligned}$$

Then A1 guarantees that $\partial v / \partial y \left(w, y_i^N \right) \geq 0$, by A3 $a_i^N < 0$, and A4 implies that the denominator is positive, so

$$\frac{\partial Y^N}{\partial \gamma_i^v} \leq 0.$$

Replacing this term in the individual output supply reaction, shows that for $n \neq i$,

$$\frac{\partial y_n^N}{\partial \gamma_i^v} \geq 0$$

so that necessarily

$$\frac{\partial y_i^N}{\partial \gamma_i^v} \leq 0.$$

We also see, that a marginal change in the fixed cost parameter γ_i^u, holding the parameter γ_i^v constant, has not effect on the Nash equilibrium. Claim (v) follows from the definition of the profit function

$$\pi_i^N \left(w, \{\gamma_n^v\}_{n=1}^N \right) = P \left(Y^N \right) y_i^N \left(w, \{\gamma_n^v\}_{n=1}^N \right) - \gamma_i^u u(w) - \gamma_i^v v \left(w, y_i^N \left(w, \{\gamma_n^v\}_{n=1}^N \right) \right)$$

which is impacted by a change in γ_i^u and γ_i^v as follow

$$\begin{aligned}
\frac{\pi_i^N}{\partial \gamma_i^u} \left(w, \{\gamma_n^v\}_{n=1}^N \right) &= -u(w) \leq 0 \\
\frac{\pi_i^N}{\partial \gamma_i^v} \left(w, \{\gamma_n^v\}_{n=1}^N \right) &= P \left(Y^N \right) \frac{\partial y_i^N}{\partial \gamma_i^v} + P' \left(Y^N \right) y_i^N \frac{\partial Y^N}{\partial \gamma_i^v} - v_i - \gamma_i^v \frac{\partial v}{\partial y_i} \frac{\partial y_i^N}{\partial \gamma_i^v} \\
&= P' \left(Y^N \right) y_i^N \frac{\partial Y_{-i}^N}{\partial \gamma_i^v} - v_i < 0,
\end{aligned}$$

where the last simplification is obtained by using firm's i first order condition for optimality. Similarly:

$$\frac{\pi_i^N}{\partial \gamma_j^v}\left(w,\left\{\gamma_j^v\right\}_{j=1}^N\right) = P'\left(Y^N\right) y_i^N \frac{\partial Y_{-i}^N}{\partial \gamma_j^v} \geq 0.$$

□

Proof of Proposition 3.

(i) As input prices are identical for both firms we skip w from most of our notations and write for instance v_1 instead of $v_1(w)$. When the cost functions are quadratic, marginal costs are linear, and for $y_i^N < y_j^N$ at Nash equilibrium, we also have

$$\begin{aligned} & \frac{\partial c_i}{\partial y}\left(w, y_i^N\right) > \frac{\partial c_j}{\partial y}\left(w, y_j^N\right) \\ \Leftrightarrow\ & \gamma_i^v \cdot \left(v_1 + v_2 y_i^N\right) > \gamma_j^v \cdot \left(v_1 + v_2 y_j^N\right). \end{aligned} \tag{4.55}$$

By convexity, $v_2 \geq 0$, we use the fact that $\gamma_i^v > 0, \gamma_j^v > 0$ and $y_j^N > y_i^N$, to conclude that this inequality is equivalent to $\gamma_i^v > \gamma_j^v$.

(ii) We use the fact that for two numbers $a \geq 0$ and b such that $a + b \geq 0$, we also have $a + b/2 \geq 0$. We identify

$$\begin{aligned} a &\equiv \left(\gamma_i^v - \gamma_j^v\right) v_1 \\ b &\equiv v_2 \cdot \left(\gamma_i^v y_i^N - \gamma_j^v y_j^N\right) \end{aligned}$$

The term a is nonnegative by (i) and A2 implies that $v_1 \geq 0$. The condition $a + b \geq 0$ corresponds to (4.55). The implied inequality $a + b/2 \geq 0$ is equivalent to claim (ii).

(iii) For $\gamma_i^v > \gamma_j^v$, the decreasing relationship A7 implies the claim:

$$e\left(\gamma_i^v\right) + \eta_i < e\left(\gamma_j^v\right) + \eta_j$$

and so, on average, $\gamma_i^u < \gamma_j^u$ and $u_i(w) < u_j(w)$.

(iv) From $\gamma_i^v > \gamma_j^v \geq 0$ and $0 \leq \mathrm{E}\left[\gamma_i^u|\gamma_i^v\right] < \mathrm{E}\left[\gamma_j^u|\gamma_j^v\right]$ we have

$$\begin{aligned}\frac{\mathrm{E}\left[\gamma_i^u|\gamma_i^v\right]}{\gamma_i^v} &< \frac{\mathrm{E}\left[\gamma_j^u|\gamma_j^v\right]}{\gamma_j^v} \Leftrightarrow \frac{e\left(\gamma_i^v\right)+\eta}{\gamma_i^v} < \frac{e\left(\gamma_j^v\right)+\eta}{\gamma_j^v} \\ &\Leftrightarrow \left(\frac{2\gamma_i^u u}{\gamma_i^v v_2}\right)^{1/2} < \left(\frac{2\gamma_j^u u}{\gamma_j^v v_2}\right)^{1/2} \\ &\Rightarrow \mathrm{E}\left[\left(\frac{2\gamma_i^u u}{\gamma_i^v v_2}\right)^{1/2}\right] < \mathrm{E}\left[\left(\frac{2\gamma_j^u u}{\gamma_j^v v_2}\right)^{1/2}\right].\end{aligned}$$

□

Proof of Proposition 4.

(i) At the LRCE characterized by (4.3), it turns out that for any active firm,

$$P(Y_{-n}^C + y) - \frac{\partial c_n}{\partial y_n}(w_n, y_n) > 0. \tag{4.56}$$

By A3(ii) this function is decreasing in y_n at the LRCE for any active firm. For maximizing W, the social planer chooses $\{y_m\}_{m=1}^M$ in order to satisfy $P\left(\sum_{m=1}^M y_m\right) - \partial c_n/\partial y_n\left(w_n, y_n, \gamma_n\right) = 0$ for any active firm, and this requires choosing $\{y_m\}_{m=1}^M$ such that $\sum_{m=1}^M y_m^W > \sum_{m=1}^M y_m^C$. Equivalently, by A1, we have $P\left(Y^W\right) < P\left(Y^C\right)$.

(ii) It follows directly from (i) and profit maximization, that:

$$\pi_n^W = P(Y^W)y_n^W - c_n\left(w_n, y_n^W\right) < P(Y^C)y_n^W - c_n\left(w_n, y_n^W\right) \leq P(Y^C)y_n^C - c_n\left(w_n, y_n^C\right) = \pi_n^C.$$

(iii)-(v) At the aggregate production level $Y^W > Y^C$ the firms' production plans have to satisfy:

$$\frac{\partial c_m}{\partial y_m}(w_m, y_m^W) = \frac{\partial c_n}{\partial y_n}(w_n, y_n^W) = P\left(Y^W\right). \tag{4.57}$$

At the LRCE, firms are characterized by:

$$\frac{\partial c_n}{\partial y_n}(w_n, y_n^C) = P'(Y^C)\left(y_n^C - y_m^C\right) + \frac{\partial c_m}{\partial y_m}(w_m, y_m^C)$$

so that bigger firms have lower marginal cost at the LRCE (just as in P1). This equation also shows how each firm n has to adjust y_n^C in order to achieve y_n^W satisfying (4.57). Let us order firms from lower to higher marginal cost, and define "bigger firms" as those having at LRCE a marginal cost lower than $P\left(Y^W\right)$, and "smaller firms" the other group with

$\partial c_n/\partial y_n\,(w_n, y_n) > P\left(Y^W\right)$.

Starting from the LRCE, the social planer requires that:

- bigger firms produce more output: $y_n^W > y_n^C$. Bigger firms with lower but increasing marginal costs, increase their production up to the point where (4.57) is satisfied (A3 ensures that such a point exists). Bigger firms with increasing returns at y_n^C cannot have global increasing returns by A3, so their production can be increased to met (4.57).
- smaller firms with increasing returns produce more if this allows to sufficiently decrease their marginal cost and reach $P\left(Y^W\right)$. If this is not possible, they are shut down.
- smaller firms with increasing marginal costs have to produce less and reduce their marginal cost in order to satisfy (4.57). If this is not possible, they should stop their activity.

(vi) In points (iii)-(v) we have identified either firms which should continue to produce at the LRWP, or firms which should be shut down. So, the first intuition is that $N^C \geq N^W$. However, it may well be the case that some firms did not enter the Cournot market due to negative profit at LRCE, while they would contribute to increase welfare. These non-entering firms are characterized by:

$$P(Y^C + y_m) + P'(Y^C + y_m)y_m = \frac{\partial c_m}{\partial y_m}(w_m, y_m), \qquad \text{and} \qquad P(Y^C + y_m) < \frac{c_m}{y_m}(w_m, y_m)$$
$$\Rightarrow \quad \frac{\partial c_m}{\partial y_m}(w_m, y_m) < P(Y^C + y_m) < \frac{c_m}{y_m}(w_m, y_m).$$

These non-entering firms have increasing returns to scale (marginal costs are below their average costs). At the LRWP, however, some of these firms should be reactivated if they are operational at the lower price and able to satisfy:

$$P(Y^W + y_m) = \frac{\partial c_m}{\partial y_m}(w_m, y_m),$$

at a fixed cost that is not too high. As the number of such non-entering firms is arbitrary it is not possible to conclude that $N^W \leq N^C$. However, we can claim (vi) whose meaning is somewhat different. □

Proof of Proposition 5.

We use the fact that the Hirschman-Herfindahl index of concentration $H\left(Y, \sum_{n=1}^N y_n^2\right)$ is nonincreasing in N and increasing when individual outputs are redistributed from smaller to bigger firms. Under decreasing returns to scale, point P4(v) vanishes, and point (vi) can be sharpen to $N^W \leq N^C$. Let us define $\kappa \equiv Y^W/Y^C$ and starting from LRCE, let us scale all individual output levels up to κy_n^C. This leaves the value of Hirschman-Herfindahl index unchanged as

$$H\left(Y^C, \sum_{n=1}^{N^C}\left(y_n^C\right)^2\right) = \sum_{n=1}^{N^C}\left(\frac{y_n^C}{Y^C}\right)^2 = \sum_{n=1}^{N^C}\left(\frac{\kappa y_n^C}{Y^W}\right)^2 = H\left(Y^W, \sum_{n=1}^{N^C}\left(\kappa y_n^C\right)^2\right).$$

Individual firms have now seen their production arbitrarily scaled up by κy_n^C, so that aggregate production is Y^W. However, in order to produce Y^W optimally, such as characterized in P4, the social planer still has to redistribute the individual output levels κy_n^C while keeping the aggregate level fixed at Y^W. We will show that this is achieved by redistributing output from smaller to bigger firms, which increases the value taken by H. We know that at LRCE

$$\frac{\partial c_n}{\partial y}(w, y_n^C) = P'(Y^C)\left(y_n^C - y_m^C\right) + \frac{\partial c_m}{\partial y}(w, y_m^C)$$

and so $y_n^C \geq y_m^C$ iff $\partial c_n/\partial y(w, y_n^C) \leq \partial c_m/\partial y(w, y_m^C)$ as in P1. By convexity, using also P3(i) and A7, we have for any value of y

$$0 \leq \frac{\partial^2 c_n}{\partial y^2}(w, y_n) = \gamma_n^v v_2(w) < \gamma_m^v v_2(w) = \frac{\partial^2 c_m}{\partial y^2}(w, y_m).$$

This inequality implies that marginal costs increase more strongly in small firms; so that if we inflate all individual outputs by multiplication with $\kappa \geq 1$ then,

$$\frac{\partial c_n}{\partial y}(w, \kappa y_n^C) \leq \frac{\partial c_m}{\partial y}(w, \kappa y_m^C),$$

which means that bigger firms have lower marginal costs at $\{\kappa y_n^C\}_{n=1}^M$ than smaller firms. The social planer wants to implement the equality:

$$\frac{\partial c_n}{\partial y}(w, y_n^W) = P(Y^W)$$

which she can achieve for all active firms by increasing further the output of the biggest firms (with lowest marginal cost), and decreasing the output of the smaller firms characterized by

$$\frac{\partial c_m}{\partial y}(w_m, \kappa y_n^C) > P(Y^W).$$

This redistribution of constant aggregate output from small to bigger firms increases the value of H. □

Proof of Proposition 6.
The parameter vector $\boldsymbol{\alpha} = g(\theta, \beta)$ is identified by the full column rank of $\boldsymbol{X}$. Under the identification assumption (4.29), the conditional mean of the cost function has an additive

decomposition:

$$c(w_{nt}, t, y_{nt}; \theta) + \phi_z(w_{nt}, t, y_{nt}, z_{nt}; \theta, \beta), \tag{4.58}$$

with ϕ_z such that $\phi_z(w_{nt}, t, y_{nt}, \bar{z}; \theta, \beta) = 0$. For $z = \bar{z}$ the model has no unobserved heterogeneity (or random unobserved heterogeneity) and all parameters θ are identified under the full rank assumption. It turns out that when z varies, this identifies ϕ_z, as well as all additional parameters β under the full rank assumption.

4.10 Appendix B: Further information on the data and descriptive statistics

4.10.1 Data cleaning

As mentioned in the main text, the industry for food processing (10), the manufacture of tobacco products (12), and the manufacture of coke and refined petroleum products (19) are excluded from the treated sample. Further, we only keep observations reporting values larger than zero in capital stock (tangible assets), number of employees, materials, and production. Table 4.11 illustrates summary statistics of a typical 4-digit industry if no data cleaning at all was made. The table shows that, compared to the case with data cleaning (Table 4.3), the average number of firms is more than doubled, given by 765. This is mainly induced by the inclusion in Table 4.11 of industry 10 and to a smaller extend by keeping firms reporting zero and missing values in the number of employees. However, the table also shows that firms with less than 10 (500 or more) employees account for about 6.2% (53.9%), which is very close to the figures presented based on the cleaned sample. Hence, our sample generally matches the main characteristics of the French manufacturing.

Table 4.11: Average statistics of a typical 4-digit manufacturing industry without data cleaning[a]

Firm size[b]	# of firms	Share of firms	Share of employees	Share of production
0	156	20.39	0.04	2.77
1	96	12.55	0.72	0.34
2-4	161	21.05	3.33	1.15
5-9	110	14.38	5.36	1.99
10-19	60	7.84	6.02	3.01
20-49	52	6.80	12.03	7.94
50-99	16	2.09	8.56	6.20
100-199	10	1.31	10.55	8.58
200-499	6	0.78	14.66	13.61
500+	3	0.39	38.71	53.91
NA	95	12.42	0.00	0.48
Total	765	100.00	100.00	100.00

[a] All figures represent averages over all 4-digit industries and years (1994-2016). Shares are given in %.
[b] Firm sizes are measured by the number of employees. The group NA represents those firms with missing values in the number of employees.

4.10.2 Further descriptive statistics

Table 4.12 shows shares of firms, employees, and production w.r.t. each considered 2-digit industry. The table shows that the manufacture of metal products (25) represents the biggest industry in terms of the average number of firms and average employment, representing about 22.4% of all firms and 13.4% of total employment. Instead, the manufacturing for motor vehicles represents the biggest industry in terms of production, accounting for about 14.6% of total production. See also De Monte (2021) for more descriptive statistics using the same data, with a particular attention on firm dynamics (entry and exit).

Table 4.12: Average statistics by 2-digit manufacturing industry[a]

Industry[b]	# of firms	Share of firms	Share of employees	Share of production
11	1,132	1.79	1.75	4.04
13	2,578	4.07	2.93	1.94
14	3,574	5.65	3.36	1.76
15	966	1.53	1.39	0.84
16	4,767	7.53	2.91	1.94
17	1,236	1.95	3.33	3.32
18	7,566	11.96	3.77	1.90
20	2,068	3.27	7.49	13.52
21	370	0.58	3.62	4.56
22	3,765	5.95	8.40	6.01
23	4,157	6.57	5.50	4.87
24	815	1.29	3.84	5.41
25	14,185	22.42	13.40	9.14
26	2,483	3.92	6.60	4.49
27	1,853	2.93	5.93	5.16
28	4,858	7.68	7.93	6.78
29	1,559	2.46	10.15	14.58
30	558	0.88	5.06	8.30
31	4,780	7.55	2.63	1.44
Total	63,270	100.00	100.00	100.00

[a] All figures are based on the cleaned dataset and represent averages over the period 1994-2016. Shares are given in %.

[b] 11-beverages, 13-textiles, 14-wearing apparel, 15-leather/related products, 16-wood/products of wood and cork, 17-paper/paper products, 18-printing/reproduction of recorded media, 20-chemicals/chemical products, 21-pharmaceutical products/preparations, 22-rubber/plastic products, 23-other non-metallic mineral products, 24-basic metals, 25-fabricated metal products, 26-computer, electronic, and optical products, 27-electrical equipment, 28-machinery and equipment, 29-motor vehicles/(semi-) trailers, 30-other transport equipment, 31-furniture.

Table 4.13 illustrates the distribution of some variables included in z_{nt} to capture unobserved heterogeneity for the estimation of the cost function (Section 4.7.2). As in the descriptive statistics section, the table reports averages in a typical 4-digit industry, as well as the distribution of firm sizes over the 1994-2016 period. Beside the average number and the average share of firms, the table reports the share of investing firms, the investment-to-labor ratio, the average firm age as well as the average number of observed periods (denoted by T_n in the main text). Note that firms' investment, i_{nt}, are given by expenditures in intangible assets, reported in the balance sheets, deflated by the corresponding 2-digit investment price index. Unfortunately, firms' investments are not observed for the specific year 2008. We replace the largest part of these missing values by computing $i_{n2008} = K_{n2009} - (1 - \delta_{2008})K_{n2008}$, where K_{nt} represents firms' intangible assets from the balance sheet, deflated by a corresponding 2-digit price index, and δ_t denotes the capital depreciation rate, likewise calculated at the 2-digit level. It can be seen that the share of investing firms is increasing in firm size, where the share of investing firms with only one employee is given by 57.6 %, whereas almost all firms with 500 and more employees report investments in capital (99.1 %). Regarding the investment-to-labor ratio there seems to be two clusters: one with an investment level of about 6,000€ (or 0.06) per worker and another cluster with average investment around 10,000€. Considering firms' average age and average number of observed periods, it can be seen that, as expected, both variables are increasing in firm size. That is, while the average age (number of observed periods) of firms with only one employee is given by 12.4 years (5 periods), the largest size group, firms reporting 500 and more employees, are on average 29.1 years old (and observed on average for 12.7 periods). Firms' age, a_{nt}, is calculated as the difference between the current year and the date of creation of the firm. So, firms' age does not necessarily correspond to the number of observed periods as especially small firms often show temporal inactivity and/or drop out of the sample because of missing values. Both variables should represent good proxies to capture unobserved heterogeneity.

Table 4.13: Further average statistics by 4-digit manufacturing industry[a]

Firm size[b]	# of firms	Share of firms	Share of investing firms	Investment-to-labor ratio	Firm age	# of obs. periods
1	50	14.71	57.63	0.11	12.37	5.04
2-4	82	24.12	68.63	0.07	13.83	7.48
5-9	73	21.47	81.95	0.06	16.79	9.51
10-19	52	15.29	90.91	0.06	19.73	10.91
20-49	49	14.41	95.42	0.06	22.98	11.56
50-99	16	4.71	97.35	0.06	25.83	11.96
100-199	9	2.65	98.14	0.08	27.14	12.29
200-499	6	1.76	98.83	0.10	27.65	12.83
500+	3	0.88	99.14	0.12	29.13	12.68
Total	340	100.00	80.07	0.07	17.77	9.15

[a] All figures are based on the cleaned dataset and represent averages over the period 1994-2016. Shares are given in %.

[b] Firm size is measured by the number of employees.

4.11 Appendix C: Reparameterization of the cost function

The relationship between the structural model and the reduced form is outlined below. We insert the linear expression of γ^j given by (4.47) into the cost function and the marginal cost function to obtain:

$$
\begin{aligned}
E[c_{nt}|w_n, t, y_n, z_{nt}] = {} & \left(1 + (z_{nt} - \bar{z})^\top \beta^u\right) \left(\theta_w^\top w + \theta_{wt}^\top wt + \frac{1}{2}\frac{w^\top \Theta_{ww} w}{\zeta^\top w}\right) \\
& + \left(1 + (z_{nt} - \bar{z})^\top \beta^v\right) \left(\theta_{1w}^\top w + \theta_{1t}^\top wt + \frac{1}{2}\frac{w^\top \Theta_{1ww} w}{\zeta^\top w}\right) y \\
& + \left(1 + (z_{nt} - \bar{z})^\top \beta^v\right) \left(\theta_{2w}^\top w\right) y^2,
\end{aligned}
$$

$$
E\left[p\left(1 + \epsilon \frac{y_{nt}}{Y_t}\right)|w_n, t, y_n, z_{nt}\right] = \left(1 + (z_{nt} - \bar{z})^\top \beta^v\right) \left(\theta_{1w}^\top w + \theta_{1t}^\top wt + \frac{1}{2}\frac{w^\top \Theta_{1ww} w}{\zeta^\top w} + 2\left(\theta_{2w}^\top w\right) y\right).
$$

We now define $\widetilde{z} \equiv z_{nt} - \bar{z}$ and $\widetilde{w} = \text{vech}(ww^\top)$ which is a vector with $J(J+1)/2$ components. We reparameterize the system which is nonlinear in (θ, γ) so that it becomes linear in $\boldsymbol{\alpha} = g(\theta, \gamma)$. For simplicity, however, we keep the notation θ below to characterize some $\boldsymbol{\alpha}$ parameters which enter linearly in the model:

$$
\begin{aligned}
E[c_{nt}|w_n, t, y_n, z_{nt}] = {} & \theta_w^\top w + \theta_{wt}^\top wt + \frac{1}{2}\frac{w^\top \Theta_{ww} w}{\zeta^\top w} \\
& + \left(\theta_{1w}^\top w + \theta_{1t}^\top wt + \frac{1}{2}\frac{w^\top \Theta_{1ww} w}{\zeta^\top w}\right) y + \left(\theta_{2w}^\top w\right) y^2 \\
& + \widetilde{z}^\top A_1 w + \widetilde{z}^\top A_2 wt + \widetilde{z}^\top A_3 wy + \widetilde{z}^\top A_4 wty + \widetilde{z}^\top A_5 wy^2 \\
& + \frac{1}{2\zeta^\top w}\left(\widetilde{z}^\top A_6 \widetilde{w} + \widetilde{z}^\top A_7 \widetilde{w} y\right).
\end{aligned}
$$

$$
\begin{aligned}
E\left[p\left(1 + \epsilon \frac{y_{nt}}{Y_t}\right)|w_n, t, y_n, z_{nt}\right] = {} & \theta_{1w}^\top w + \theta_{1t}^\top wt + \frac{1}{2}\frac{w^\top \Theta_{1ww} w}{\zeta^\top w} + 2\left(\theta_{2w}^\top w\right) y \\
& + \widetilde{z}^\top A_3 w + \widetilde{z}^\top A_4 wt + 2\widetilde{z}^\top A_5 wy + \frac{1}{2\zeta^\top w}\widetilde{z}^\top A_7 \widetilde{w}.
\end{aligned}
$$

Note that all parameters of the marginal cost function are also included in the cost function, and imposing these restrictions helps identifying the cost parameters.

These relationships show that the parameters of the cost function are separately identified from the parameters of the γ^j function. It can also be seen that a simple test for the hypothesis of random (uncorrelated) heterogeneity consists to test whether $A_j = 0$ for $j = 1, \ldots, 7$. We report the results of such a test is Table 4.6. It is possible to test separately for the hypothesis of random (uncorrelated) heterogeneity in the fixed cost or in the variable cost by respectively considering whether $A_1 = A_2 = 0$ and $A_6 = 0$ or whether $A_3 = A_4 = A_5 = 0$ and $A_7 = 0$. In order to conserve some parsimony, we restrict the A_j coefficients associated with explanatory variables which are the same for all firms to be equal to zero (coefficients associated with w_k, w_m and t).

Chapter 5

On nonparametric instrumental regression with additive fixed effects[1]

5.1 Introduction

This chapter addresses nonparametric estimation of panel data models with endogeneity in the explanatory variable. In particular, it develops an estimator that combines nonparametric instrumental regression with a local-within fixed effect estimator.

In applied econometrics, when estimating structural models, one of the biggest difficulties to overcome is endogeneity in the explanatory variables. With panel data, the use of fixed effects (FE) estimators, i.e. within or first-differences, allows to control for some potential sources of endogeneity when a specific part of the error component is related to the explanatory variables. Often, however, this does not suffice, since the remaining error term might still be correlated with the regressors. This would be the case if, for instance, the underlying structural model stems from a market equilibrium model, such as the inverse product demand function used in industry competition models (Hopenhayn, 1992; Amir and Lambson, 2003; Esponda and Pouzo, 2019; De Monte and Koebel, 2021). More precisely, the inverse product demand function describes the price mechanism of an industry and maps production levels into prices. Theoretically, prices and production levels are inversely related, i.e. a higher production level should translate into lower prices, which is also known as the law of demand - one of the most fundamental concepts in economics. Empirically, prices might not only shift by changing production levels but also by macroeconomic and industry specific shocks. Since these shocks are difficult to model and likely to be correlated with the production level, they are often taken into account by unobserved FE. Moreover, the explanatory variable (production) is jointly determined with the dependent variable (prices) by the market equilibrium mechanism, leading to simultaneity bias when not taken into account (Wooldridge, 2016, Chapter 16).

[1] This chapter is based on De Monte, E. (2021), On nonparametric instrumental regression with additive fixed effects, *mimeo, BETA, Université de Strasbourg.* (Submitted)

In such a case both instrumental variable (IV) and FE regression techniques should be applied to cope with all sources of endogeneity. For parametric (especially linear) models this is a common estimation and identification strategy. See, for instance, Ziliak (1997) comparing different panel data estimators as well as Koebel and Laisney (2016) and De Monte and Koebel (2021) for applications in the estimation of the inverse demand in the context of a Cournot competition model. However, if the functional form of the parametric model is misspecified, the estimator combining IV and FE regression will still be inconsistent and biased. To avoid misspecification issues, nonparametric methods are promising. In this field much work has been done concerning both nonparametric FE and IV regression. For instance, concerning nonparametric FE regression, Su and Ullah (2006) develop a nonparametric profile likelihood estimator with FE, Henderson et al. (2008) present an iterative kernel estimator to account for FE, and the method presented by Qian and Wang (2012) is based on marginal integration and first difference. Also see Linton and Nielsen (1995) for foundations of the concept of marginal integration, as well as Azomahou et al. (2006) presenting an application of that approach, dealing with a nonparametric panel model with additive FE to estimate the environmental Kuznets curve. Most of the mentioned approaches use global within or global first-difference to account for FE , i.e. canceling out the unobserved FE by subtracting either the global mean (computed over the whole range of the explanatory variable) or a lagged period. In this context, Lee et al. (2019) show that when applying global within or, equivalently, global first-difference estimation, a bias is introduced that is non-degenerating even for very large T. They suggest a nonparametric kernel estimator using the concept of local-demeaning or local-first-difference to avoid this bias. Also see Parmeter and Racine (2019) and Rodriguez-Poo and Soberon (2017) for a survey on panel data models considering both nonparametric and semiparametric frameworks.

Regarding to nonparametric instrumental regression important progress has been achieved, too. Here, the main challenge is to overcome the ill-posed inverse problem to solve for the nonparametric function of interest.[2] For this purpose, Newey and Powell (2003) present a nonparametric 2-stage least-squares estimator. Hall and Horowitz (2005) use a ridge-type regularization method in combination with kernel regression methods and Darolles et al. (2011) use the Tikhonov regularization to solve the ill-posed inverse problem. Horowitz (2011) further discusses this kind of estimators by comparing them to their parametric counterparts. Also see Florens et al. (2012) for the extension of instrumental regression to the case of partially linear models. Florens et al. (2018) discuss nonparametric IV regression where the interest lies on derivative estimation, using the Landweber–Fridman regularization to handle the ill-posed inverse problem. Centorrino et al. (2017) discuss the implementation and application as well as the MSE-performance w.r.t. the different regularization methods to overcome the inverse ill-posed problem. An application of nonparametric instrumental

[2] The ill-posed inverse problem in this context will be discussed in the following sections.

IV regression is brought by Blundell et al. (2007) for the case of the estimation of the Engel curve.[3] Combining nonparametric IV regression with FE, the only paper filling this gap, to my knowledge, is presented by Fève and Florens (2014). They use the Tikhonov regularization, which states the IV-part in the estimation procedure and, to control for unobserved FE, Fève and Florens (2014) rely on first-difference.

In this chapter I propose an alternative estimator to the one presented by Fève and Florens (2014), i.e. a nonparametric instrumental estimator for the estimation of the conditional mean function while controlling for unobserved FE. More specifically, the estimator combines the Landweber-Fridman regularization approach with the local-within kernel estimator presented by Lee et al. (2019) (LMU, henceforth) to control for unobserved effects. As mentioned, the estimator is interesting since it avoids problems related to the non-degenerating bias described in Lee et al. (2019), occurring when using global first-difference/within estimation. Also, the estimator allows for flexibility of treating different kind of panel models with endogeneity, i.e. to control for either individual, temporal or two-ways effects (when both individual and temporal FE are simultaneously taken into account). The estimator is applied on simulated data, incorporating a panel model with two-way effects, where a Monte Carlo simulation reveals a good finite sample behavior. Moreover, to illustrate the applicability of the estimator on real data, I estimate the inverse product demand function relying on U.S. data used in Koebel and Laisney (2016) to estimate a parametric inverse demand model. The data contains price and production level observations of 21 2-digits manufacturing industries, covering the period from 1949 to 2001. The results show that prices are not always decreasing in production, which indicates a violation of the law of demand and points to potential misspecification issues when using parametric models. In addition, I find that the pointwise estimate of the inverse demand changes considerably depending on the instrument in use.

The chapter is organized as follows: Section 5.2 discusses related estimation methods, Section 5.3 presents the alternative estimation procedure, Section 5.4 illustrates the performance of the proposed estimator on simulated data, Section 5.5 exemplifies its application by the estimation of an inverse demand function, and Section 5.6 concludes.

5.2 Related estimation methods

In this section I briefly present the nonparametric estimator proposed by Fève and Florens (2014) that involves nonparametric IV regression with FE. This illustrates the current approach for treating panel models endogenous variables and allows to see the difference to

[3] Note that various statistical softwares already provide tools to conduct nonparametric instrumental regression as, for instance, the Comprehensive **R** Archive Network (CRAN) and **Stata** (Racine and Hayfield, 2020; Hayfield and Racine, 2008; Chetverikov et al., 2018).

my approach shown in Section 5.3. Further down in this section I present the nonparametric FE estimator presented by Lee et al. (2019), which does not contain an IV component. The understanding of this estimator is crucial as I will make extensive use of it in the estimation procedure of my approach.

5.2.1 Fève and Florens (2014)'s estimator: instrumental regression with FE

Fève and Florens (2014) consider a panel model given by

$$Y_t = \varphi(Z_t) + \xi + U_t, \quad t = 1, \dots, T \tag{5.1}$$

with the i.i.d. observations $\{y_{it}, z_{it}\}_{i,t=1}^{n,T}$ and ξ an unobserved individual effect that is possibly endogenous. Note that both ξ and U_t can be correlated with $Z_1, \dots, Z_T$ in this setup. This is compatible with simultaneity on markets where both Y_t and Z_t are endogenous and correlated with U_t. Furthermore, W denotes a set of valid instruments. To control for the unobserved individual effect, Fève and Florens (2014) apply first difference, yielding

$$Y_t - Y_{t-1} = \varphi(Z_t) - \varphi(Z_{t-1}) + U_t - U_{t-1}, \quad t = 2, \dots, T \tag{5.2}$$

where $E(U_t - U_{t-1}|W) = 0$ is assumed. Consider in the following a two-period example with $t = 1$ and $t = 2$. Under some assumptions the conditional expectation operator is well defined and given by[4,5]

$$K\varphi = r, \tag{5.3}$$

where $(K\varphi)(w) = E(\varphi(Z_2) - \varphi(Z_1)|W = w) \in \mathbb{L}^2_W$ and $r(w) = E(Y_2 - Y_1|W = w) \in \mathbb{L}^2_W$.[6] That is, K is a conditional mean operator projecting functions of Z onto the space of W, i.e. $K : \mathbb{L}^2_Z \longrightarrow \mathbb{L}^2_W$. Hence, $(K\varphi)(w)$ can be expressed by

$$(K\varphi)(w) = \int \varphi(z) \frac{f_{Z_2,W}(z,w) - f_{Z_1,W}(z,w)}{f_W(w)} dz, \tag{5.4}$$

which is a Fredholm equation of the first kind (Fredholm et al., 1903).

Consider again equation (5.3), by iterating the projection onto the space of the endogenous variable Z, one obtains

$$K^* K\varphi = K^* r, \tag{5.5}$$

[4] In particular, Fève and Florens (2014) consider a density π of a probability and assume that $\varphi \in \mathcal{E} = \{\varphi : \mathbb{R}^p \to \mathbb{R} / \int \varphi^2(z)\pi(z)dz < \infty \text{ and } \int \varphi(z)\pi(z)dz = 0\}$. The density π is such that $\mathcal{E} \subset \mathbb{L}^2_{Z_t}$, for $t = 1, 2$.

[5] Note that Fève and Florens (2014) also develop in the appendix of the paper a generalization of their estimator for T periods. To present their estimator I here keep the two-periods example.

[6] The shorthand notation as, for example, $E(Y|Z = z) = E(Y|z)$ will also be used in following conditional expectation expressions. That is, $E(Y|z)$ tells us that a random variable Y is conditioned on z, i.e., on any point belonging to the conditioning random variable Z.

where K^* is an adjoint conditional expectation operator projecting functions of W onto the space of function of Z, i.e. $K^* : \mathbb{L}^2_W \longrightarrow \mathbb{L}^2_Z$. Equation (5.5) defines the estimator for φ, which can be seen as the solution of a large system of equation exposed to singularity in finite samples (Centorrino et al., 2017). This is why the inversion of K^*K is generally infeasible and thus referred to an ill-posed inverse problem. See Florens (2003), Carrasco et al. (2007), and Horowitz (2014) for detailed discussions on ill-posed inverse problems. To circumvent the ill-posedness Fève and Florens (2014) propose to apply the Tikhonov regularization (Tikhonov and Arsenin, 1977) which seeks to minimize

$$||K\varphi - r||^2 + \alpha||\varphi||^2 \tag{5.6}$$

w.r.t. φ, where $\alpha > 0$ is a regularization parameter to be chosen by the user, and with

$$||\varphi||^2 = \int \varphi^2(z)\pi(z)dz. \tag{5.7}$$

The solution to (5.6) is then given by

$$\varphi^\alpha = (\alpha I + K^*K)^{-1}K^*r. \tag{5.8}$$

The intuition of Tikhonov regularization is to add the constant α to the eigenvalues of K^*K which in turn allows for inversion. Then, the last equation becomes

$$\alpha\varphi^\alpha(z) + \int \varphi^\alpha(t)a(t,z)dt = \int yb(y,z)dy \tag{5.9}$$

where

$$a(t,z) = \frac{1}{\pi(z)} \int \frac{1}{f_W(w)} \Big(f_{Z_2,W}(z,w) - f_{Z_1,W}(z,w)\Big)\Big(f_{Z_2,W}(t,w) - f_{Z_1,W}(t,w)\Big)dw \tag{5.10}$$

and

$$b(y,z) = \frac{1}{\pi(z)} \int \frac{f_{Y,W}(y,w)}{f_W(w)} \Big(f_{Z_2,W}(z,w) - f_{Z_1,W}(z,w)\Big)dw. \tag{5.11}$$

The estimator for φ^α is then given by the solution to (5.9) by replacing the functions $a(\cdot)$ and $b(\cdot)$ by appropriate kernel density estimates of the densities $f_{Z_2,W}$, $f_{Z_1,W}$, $f_{Y,W}$, and f_W.

5.2.2 Lee et al. (2019)'s estimator: FE only

The motivation for the local-within kernel estimator proposed by Lee et al. (2019) lies in the fact, as they prove, that global-demeaning or global first difference to remove the unobserved individual effect - as it is practiced in many studies as well as in the estimation procedure in Fève and Florens (2014) - introduces a non-degenerating bias. Instead, removing the individual effect locally, i.e. by local-within or local-first-difference, allows to remove this bias. To present this approach, I maintain the notation used by the authors, which differs from the previous section. From now on, random variables belonging to the regression model are indexed by the individual and time dimensions (i, t), since the notation is suitable for the development of the estimator. Lee et al. (2019) consider the following panel model, here for simplicity only the univariate case:

$$Y_{it} = \varphi(Z_{it}) + \xi_i + U_{it} \tag{5.12}$$

where φ is an unknown Borel measurable function with the necessary identification assumption $\varphi(0) = 0$, ξ_i is an unobserved individual effect potentially correlated with the regressor variable Z_{it}. The difference to the panel model presented in Section 5.2.1 is that the error component U_{it} is supposed to be uncorrelated with Z_{it}, hence, we only need to care about the unobserved FE, without further need of IV methods. The model assumptions imply

$$E(Y_{it}|Z_{it}, \xi_i) = \varphi(Z_{it}) + \xi_i \quad i = 1, \dots, n \;\; t = 1, \dots, T. \tag{5.13}$$

In their approach, the main interest lies in the estimation of the marginal change in the conditional mean of Y_{it} w.r.t. an interior point of Z_{it} denoted by z. That is,

$$\beta_1(z) = \frac{\partial \varphi}{\partial z}(z). \tag{5.14}$$

A Taylor expansion around z yields the objective function to be minimized w.r.t. β_0 and β_1,

$$Q_{nT}(\beta_0, \beta_1, \xi_1, \dots, \xi_n) = \sum_{i=1}^{n} \sum_{t=1}^{T} \{Y_{it} - \beta_0 - \beta_1(Z_{it} - z) - \xi_i\}^2 C_h(Z_{it} - z), \tag{5.15}$$

where C is a kernel function and h the bandwidth parameter. To remove ξ_i, Lee et al. (2019) concentrate the objective function and consider

$$Q^c_{nT}(\beta_1) = \sum_{i=1}^{n} \sum_{t=1}^{T} \{Y^*_{it}(z) - \beta_1 Z^*_{it}(z)\}^2 C_h(Z_{it} - z) \tag{5.16}$$

with the locally-demeaned variables

$$Y^*_{it}(z) = Y_{it} - \sum_{s=1}^{T} Y_{is} \mathbf{w}_{is}(z) \tag{5.17}$$

with the weight $\mathbf{w}_{is}(z) = C_h(Z_{is} - z) / \sum_{r=1}^{T} C_h(Z_{ir} - z)$ and the same transformation for $Z_{it}^{*}(z)$.[7] Two properties of the weight are important to mention: (i) $\mathbf{w}_{it}(z) \geq 0 \; \forall \; t$ and (ii) $\sum_{t=1}^{T} \mathbf{w}_{it}(z) = 1$.

The estimate for the first gradient, $\beta_1(z)$, is then obtained as the solution to minimizing (5.16), given by

$$\beta_1(z) = \left\{ \sum_{i=1}^{n} \sum_{t=1}^{T} Z_{it}^{*}(z) Z_{it}^{*}(z) C_h(Z_{it} - z) \right\}^{-1} \sum_{i=1}^{n} \sum_{t=1}^{T} Z_{it}^{*}(z) Y_{it}^{*}(z) C_h(Z_{it} - z). \tag{5.18}$$

In a second step, by imposing $\varphi(0) = 0$, Lee et al. (2019) show that the conditional mean function $\varphi(z)$ can be recovered and estimated by

$$\widehat{\varphi}(z) = \frac{1}{n} \sum_{n=1}^{n} \{ \widehat{\gamma}_i(z) - \widehat{\gamma}_i(0) \} \tag{5.19}$$

with

$$\widehat{\gamma}_i(z) = \sum_{t=1}^{T} \{ Y_{it} - \widehat{\beta}_1(z)(Z_{it} - z) \} w_{it}(z). \tag{5.20}$$

A very useful feature of this estimator is that it is easily extendable to the case of a two-ways effect model, such as given below

$$Y_{it} = \varphi(Z_{it}) + \xi_i + \delta_t + \epsilon_{it}, \tag{5.21}$$

where ξ_i and δ_t are unobserved individual and temporal effects, potentially correlated with the regressor Z_{it}. To control for the unobserved effects one needs simply to replace $Y_{it}^{*}(z)$ in (5.18) by $Y_{it}^{**}(z)$, defined by

$$Y_{it}^{**}(z) = Y_{it} - \sum_{s=1}^{T} \mathbf{w}_{is}^{a}(z) Y_{is} - \sum_{j=1}^{n} \mathbf{w}_{jt}^{b}(z) Y_{jt} + \sum_{j=1}^{n} \sum_{s=1}^{T} \mathbf{w}_{js}^{c}(z) Y_{js} \tag{5.22}$$

with

$$\mathbf{w}_{is}^{a}(z) = \frac{C_h(Z_{is} - z)}{\sum_{r=1}^{T} C_h(Z_{ir} - z)}, \quad \mathbf{w}_{jt}^{b}(z) = \frac{C_h(Z_{jt} - z)}{\sum_{k=1}^{n} C_h(Z_{kt} - z)} \quad \mathbf{w}_{js}^{c}(z) = \frac{C_h(Z_{js} - z)}{\sum_{k=1}^{n} \sum_{r=1}^{T} C_h(Z_{kr} - z)}. \tag{5.23}$$

and similarly to obtain $Z_{it}^{**}(z)$. Note that necessary conditions to obtain the estimate for the conditional mean are $\varphi(0) = 0$ as well as $\sum_{t=1}^{T} \mathbf{w}_{it}^{a}(z) = 1$, $\sum_{i=1}^{n} \mathbf{w}_{it}^{b}(z) = 1$ and $\sum_{i=1}^{n} \sum_{t=1}^{T} \mathbf{w}_{it}^{c}(z) = 1$ and where all weights are comprised between 0 and 1.

[7] Note that Lee et al. (2019) present a very similar procedure for local-first difference.

A pointwise estimate of the conditional mean function $\widehat{\varphi}(z)$ is then obtained by

$$\widehat{\varphi}(z) = \frac{1}{n}\sum_{i=1}^{n}\left\{\widehat{\gamma}_i^a(z) - \widehat{\gamma}_i^a(0)\right\} + \frac{1}{T}\sum_{t=1}^{T}\left\{\widehat{\gamma}_t^b(z) - \widehat{\gamma}_t^b(0)\right\} - \left\{\widehat{\gamma}^c(z) - \widehat{\gamma}^c(0)\right\} \tag{5.24}$$

with

$$\begin{aligned}
\widehat{\gamma}_i^a(z) &= \sum_{t=1}^{T}\left\{Y_{it} - \widehat{\beta}_1(z)(Z_{it} - z)\right\}\mathbf{w}_{it}^a(z), \\
\widehat{\gamma}_t^b(z) &= \sum_{i=1}^{n}\left\{Y_{it} - \widehat{\beta}_1(z)(Z_{it} - z)\right\}\mathbf{w}_{it}^b(z), \\
\widehat{\gamma}^c(x) &= \sum_{i=1}^{n}\sum_{t=1}^{T}\left\{Y_{it} - \widehat{\beta}_1(x)(Z_{it} - z)\right\}\mathbf{w}_{it}^c(z).
\end{aligned} \tag{5.25}$$

Here, $\widehat{\beta}_1(z)$ is obtained by local linear regression based on $\{Y_{it}^{**}(z), Z_{it}^{**}(z)\}_{n,T=1}^{n,T}$. Also note that the derivation of (5.24) is not presented in the paper of Lee et al. (2019) but relies on own calculations. Details on optimal bandwidth selection via leave-one-out cross-validation for the estimation of conditional mean function $\varphi(z)$ are provided in Appendix 5.7.

5.3 Another estimation procedure for instrumental regression with FE

This section presents and alternative estimator to the one presented Fève and Florens (2014). For this purpose, the Landweber-Fridman regularization method for nonparametric instrumental regression is combined with the nonparametric FE estimator presented by Lee et al. (2019). This yields a new estimator that is more flexible w.r.t the underlying panel model specification, i.e. comprising either individual, temporal or two-ways effects, which is the prior motivation of this chapter.

5.3.1 Setup of the estimator

Consider the panel model, for simplicity with only one covariate, given by

$$Y_t = \varphi(Z_t) + \xi + U_t, \quad t = 1, \dots, T \tag{5.26}$$

with the *i.i.d.* observations $\{y_{it}, z_{it}\}_{i,t=1}^{n,T}$. The function of interest φ is supposed to belong to the space of square integrable functions of Z, denoted by $\mathbb{L}_z^2$. The explanatory variable Z_t is potentially correlated with the individual unobserved effect, ξ, as well as with the error term U_t. If there exists an instrument W satisfying $E(U_t|W = w) = E(U_t|w) = 0$, we can write

$$E(Y_t - \varphi(Z_t) - \xi|w) = 0, \tag{5.27}$$

where, given this characterization, $\varphi(Z_t)$ is the solution of a Fredholm integral equation of the first kind.[8] Given the joint density $f(y, z, \xi, w)$ and using the common abuse of notation f for denoting different densities, (5.27) can be expressed as

$$\int \varphi(z)\frac{f(w,z)}{f(w)}dz + \int \xi\frac{f(w,\xi)}{f(w)}d\xi - \int y\frac{f(w,y)}{f(w)}dy = 0, \tag{5.28}$$

where the middle integral is infeasible since ξ is unobserved. Further, let $K\widetilde{\varphi} = E(\varphi(Z_t) + \xi|w)$, with $\widetilde{\varphi}(Z_t) \equiv \varphi(Z_t) + \xi$ and $r = E(Y_t|w)$. Just as presented in Section 5.2.1, K denotes the conditional expectation operator, projecting functions of Z onto the space of functions of W, i.e. $K : \mathbb{L}^2_z \longrightarrow \mathbb{L}^2_w$ (Centorrino et al., 2017). Then, equation (5.27) can be expressed by

$$K\widetilde{\varphi} - r = 0. \tag{5.29}$$

The task at hand is now so solve (5.29) for $\widetilde{\varphi}$ - which is an ill-posed inverse problem - while recovering φ. The ill-posed inverse problem here again arises since the inversion of the operator K, to solve for φ, is discontinuous, which leads to inconsistent estimates when not regularized. To deal with the ill-posed inverse problem I make use of the Landweber-Fridman regularization (Landweber, 1951; Fridman, 1965), where I follow Racine (2019, p. 282). As will be shown, the motivation to use the Landweber-Fridman instead of the Tikhonov regularization, is that it allows to combine nonparametric instrumental regression with the local-within LMU estimator to control for the unobserved FE.

Let K^* be the adjoint conditional mean operator of K projecting functions of W onto the space of functions of Z_t, i.e. $K^* : \mathbb{L}^2_w \longrightarrow \mathbb{L}^2_z$. [9] Considering equation (5.29), take the scalar product with respect to K^*, and multiply with a constant c gives

$$cK^*K\widetilde{\varphi} = cK^*r,$$

[8] See footnote 6 for details on the used notation.

[9] It should be noted that the properties of the operators K and K^* are crucial. In particular, we need to assume that K and K^* are compact and injective, where injectivity refers to the completeness condition which is required for identification in nonparametric IV regression settings (Carrasco et al., 2007; Darolles et al., 2011; Johannes et al., 2011). Completeness involves the condition that $E(\varphi(Z)|w) = 0$ almost surely implies $\varphi(Z) = 0$. Discussions on the completeness condition can be found in Carrasco et al. (2007), Darolles et al. (2011), and Horowitz (2014). However, Freyberger (2017) showed that consistent estimates can be achieved even if completeness is not given.

or equivalently

$$\begin{aligned}\widetilde{\varphi} - cK^*K\widetilde{\varphi} &= \widetilde{\varphi} - cK^*r \\ (I - cK^*K)\widetilde{\varphi} &= \widetilde{\varphi} - cK^*r \\ \widetilde{\varphi} &= (I - cK^*K)\widetilde{\varphi} + cK^*r \\ \widetilde{\varphi} &= \widetilde{\varphi} + cK^*(r - K\widetilde{\varphi}).\end{aligned}$$

Using the Landweber-Fridman regularization, setting $c < 1$, $\widetilde{\varphi}$ can be obtained in an iterative manner, by

$$\widetilde{\varphi}_k = \widetilde{\varphi}_{k-1} + cK^*_{k-1}(r - K_{k-1}\widetilde{\varphi}_{k-1}) \tag{5.30}$$

and so

$$\varphi_k(z) + \xi = \varphi_{k-1}(z) + \xi + cE\left(E\left(Y_t - \varphi_{k-1}(Z_t) - \xi|w\right)|z\right), \tag{5.31}$$

for $k = 1, \dots, \bar{k}$ iterations, with $\bar{k}$ the total number of iterations, determined by a stopping rule described in the following sub-section. Note that, in contrast to the Tikhonov regularization used in Fève and Florens (2014), the Landweber-Fridman regularization does not aim to invert K^*K but avoids its inversion using instead the above presented iterative scheme.

5.3.2 Estimation and implementation

Estimation algorithm

The Landweber-Fridman regularization method consists in estimating the conditional mean function $\varphi(Z_t)$ over several iterations, where each iteration k, unless stopped, yields an estimate for $\varphi_k(z)$ from equation (5.31). That is, the last iteration, $\bar{k}$, should yield $\varphi_{\bar{k}}(z) \approx \varphi(Z_t)$. As can be seen, $\varphi_k(z)$ contains various conditional mean objects which, step-by-step, need to be consistently estimated to finally obtain $\varphi_k(z)$. To achieve this objective, I use the estimator proposed by LMU allowing to control for the unobserved FE ξ. It is noteworthy to mention here that when referring to the LMU estimator, I refer to the estimator presented in equation (5.19). Instead, if the model was presented as a two-ways effects model, i.e. with an individual and a temporal specific effect, the estimation routine would be the same, with the only difference that the used LMU estimator refers to equation (5.24). The estimation algorithm is described hereafter, which is followed by a discussion.

Step 1. Compute the initial guess $\widehat{\varphi}_0(z)$ by regressing Y_t on Z_t, using the LMU estimator.

Step 2. Compute $\widehat{E}\left(\widetilde{Y}_t|w\right)$ with $\widetilde{Y}_t \equiv Y_t - \widehat{\varphi}_0(Z_t)$. That is, regress $\widetilde{Y}_t$ on W, using the LMU estimator.

Step 3. Compute $\widehat{E}\left(\widehat{E}\left(\widetilde{Y}_t|w\right)|z\right)$. That is, regress $\widehat{E}\left(\widetilde{Y}_t|w\right)$, obtained from the previous step, on Z_t, using the LMU estimator.

Step 4. Compute $\widehat{\varphi}_1(z) = \widehat{\varphi}_0(z) + c\widehat{E}\left(\widehat{E}\left(\widetilde{Y}_t|w\right)|z\right)$.

Step 5. Repeat steps 2 - 4, replacing $\widehat{\varphi}_0(z)$ by $\widehat{\varphi}_1(z)$ to compute $\widehat{\varphi}_2(z)$ and so on.

Step 6. This is continued until the stopping criterion given by

$$\left\|\frac{\left(\widehat{E}(Y_t|w) - \widehat{E}(\widehat{\varphi}_k(Z_t)|w)\right)}{\widehat{E}(Y_t|w)}\right\|^2 \tag{5.32}$$

stabilizes throughout the iterations.

5.3.3 Discussion

Estimation steps

Step 1. To start the iterative scheme we first need an initial guess for $\widehat{\varphi}(z)$, the function we aim to estimate. A possibility is to use $\widehat{\varphi}_0(z) = \widehat{E}(Y_t|z)$ as a first guess.[10] However, if we simply regressed Y_t on Z_t using conventional nonparametric kernel regression, we would obtain the biased estimate of $\widehat{\varphi}_0(z)$ since in this case $E(Y_t|z) = \varphi_0(z) + E(\xi|z) \neq \varphi_0(z)$. Instead, the LMU estimator allows to consistently estimate $\varphi_0(z)$ by taking into account the unobserved effect, i.e. $E(\xi|z) \neq 0$.
Step 2. Theoretically, one can consider that $E\left(\widetilde{Y}_t|w\right) = \varphi_w(w) + E(\xi|w)$, where $\varphi_w(w)$ is the conditional mean function we aim to estimate in this step. Given that $E(\xi|w) \neq 0$, simply regressing $\widetilde{Y}_t$ on W would yield biased estimates. That is, only if the assumption $E(\xi|w) = 0$ is satisfied by the data, conventional local-linear regression can here be used, otherwise the LMU estimator should be employed to obtain an unbiased estimate for $\varphi_w(w)$.
Step 3. Theoretically, $E\left(E\left(\widetilde{Y}_t|w\right)|z\right) = \varphi_{w|z}(z) + E(\xi|z)$, where in this step $\varphi_{w|z}(z)$ is the conditional mean function we aim to consistently estimate by regressing the fitted values of $E\left(\widetilde{Y}_t|w\right)$ on Z_t. Since we must assume that $E(\xi|z) \neq 0$, i.e. prevailing unobserved FE, a consistent estimate of $\varphi_{w|z}(z)$, can only be achieved using the LMU estimator.
Step 4. For $k = 1$ we have now an estimate of equation (5.31), while having controlled for the unobserved effects ξ, and hence a direct estimate for $\varphi_1(z)$.
Step 6. Here $\widehat{E}(Y_t|w)$ can be computed before the algorithm starts by regressing Y_t on W using the LMU estimator.

[10] Note that $\widehat{E}(\cdot|\cdot)$ denotes the estimated conditional mean $E(\cdot|\cdot)$.

Bandwidth selection

As described above, in each iteration of the Landweber-Fridman regularization, various nonparametric conditional mean estimates are required. Generally, it would be desirable to use for each of these estimations optimal bandwidths by applying, for instance, leave-one-out cross-validation (see Appendix 5.7). Florens et al. (2018) show that the use of updated bandwidths, i.e. computing optimal bandwidths in each of the iterations, leads to higher accuracy of the final estimate. However, this procedure is computationally very time intensive. By this reason, for the estimates presented in this chapter, I only compute cross-validated bandwidths for the conditional mean objects of the first iteration and use them for all successive iterations.

Number of iterations

The number of iterations is here determined by the stopping rule given in (5.32). That is, when this criterion stabilizes throughout the iterations, the algorithm stops. Another possibility is to conduct a sufficient number of iterations and analyze subsequently at which iteration the stopping criterion has reached its minimum (Centorrino et al., 2017). As will be shown later in the chapter, for the application of the estimator on the simulated data, the algorithm stops when the stopping criterion stabilizes. Instead, for the estimation of the inverse demand function I run about 20 iterations and use as final estimate the one where the stopping criterion reached its minimum.[11]

5.4 Simulation and finite sample behavior

This section aims to study the performance and the finite sample behavior of the proposed estimator. To illustrate its flexibility I consider a two-ways effects model given by

$$Y_t = \varphi(Z_t) + \xi + \delta_t + U_t, \tag{5.33}$$

where the conditional mean function φ is a function of the endogenous variable Z_t, correlated with the individual and temporal specific effects, denoted by ξ and δ_t, as well as with the error U_t. W is a valid instrument satisfying $E(U_t|W) = 0$. In the following, the data generating process (DGP) is presented to obtain the observations $\{y_{it}, z_{it}, w_{it}\}$. I then apply the estimator on the simulated data and discuss the estimation results graphically. Further down, a Monte Carlo simulation studies the estimator's convergence and finite sample behavior based on different sample sizes.

[11] Centorrino (2017) shows that the optimal number of iterations can also be obtained by using the concept of cross-validation.

5.4.1 Data Generating Process (DGP)

I extend the DGP presented in Darolles et al. (2011) to the case of endogeneity characterized by correlation between the explanatory variable and both the error term and the unobserved two-ways FE. More precisely, I generate a panel dataset setting $n = 100$ and $T = 20$, yielding $nT = 2000$ observations. The unobserved FE are generated by[12]

$$\xi_i \sim \mathcal{U}(0, 1.5) \quad i = 1, \ldots, n \quad \text{and} \tag{5.34}$$

$$\delta_t \sim \mathcal{U}(0, 1.7) \quad t = 1, \ldots, T. \tag{5.35}$$

Next, an auxiliary explanatory variable $\widetilde{z}_{it}$ is generated as a function of the FE, given by

$$\widetilde{z}_{it} \sim \mathcal{N}(\xi_i + \delta_t, 1) \quad i = 1, \ldots, n, \ t = 1, \ldots, T. \tag{5.36}$$

From these draws, the instrumental variable w_{it} is generated by

$$w_{it} = \rho_{zw}\widetilde{z}_{it} + v_{w,it}, \tag{5.37}$$

where $\rho_{zw} = 0.2$ denotes the correlation coefficient between the explanatory and the instrumental variable, and $v_{w,it} \sim \mathcal{N}(0, 0.15)$ denotes and error term. Only now the generation of the endogenous explanatory variable is completed by

$$z_{it} = \widetilde{z}_{it} + v_{z,it}, \tag{5.38}$$

where $v_{z,it} \sim \mathcal{N}(0, 0.8)$. Finally, the dependent variable y_{it} is obtained by

$$y_{it} = \varphi(z_{it}) + \xi_i + \delta_t + u_{it}, \tag{5.39}$$

where $\varphi(z_{it}) = z_{it}^2$ refers to the true DGP and $u_{it} = \rho_{uz}v_{z,it} + \epsilon_{it}$, with $\rho_{uz} = 0.8$ and $\epsilon_{it} \sim \mathcal{N}(0, 0.05)$.

Table 5.1 presents the covariance matrix to illustrate the introduced endogeneity. As can be seen, the endogenous explanatory variable z_{it} is correlated with all other important components, i.e. with the instrument, w_{it}, with the unobserved individual and temporal effects, ξ_i and δ_t, as well as with the error term, u_{it}. Note that the instrument is also slightly correlated with the individual/temporal effects but uncorrelated with the error term, which is necessary to serve as a valid instrument.

[12] $\mathcal{U}$ and $\mathcal{N}$ refer to the uniform and normal distribution, respectively.

Table 5.1: Covariance between observables and unobservables

	z_{it}	w_{it}	ξ_i	δ_t	u_{it}
z_{it}	1.00	0.27	0.19	0.25	0.52
w_{it}		1.00	0.04	0.05	0.00
ξ_i			1.00	0.00	-0.01
δ_t				1.00	0.01
u_{it}					1.00

Note: I use the statistical software **R** to generate and treat the data. Random draws were obtained by specifying $set.seed(49)$.

5.4.2 Estimation results

Figure 5.1 illustrates the regularized solution path to obtain the final estimate. The initial guess estimate, i.e. $\widehat{\varphi}(z)_0$, is indicated by the bottom solid blue line. The iterative estimation procedure then approaches the true conditional mean function $\varphi(z)$, indicated by the dashed red line. The estimation resulting from the last iteration, indicated by the green line, corresponding to $\widehat{\varphi}(z)_{\overline{k}}$, is then very close to the true curve, i.e. the DGP. For better visibility, Figure 5.2 only shows the initial guess (blue line) as well as the last estimate of the iteration (green line).

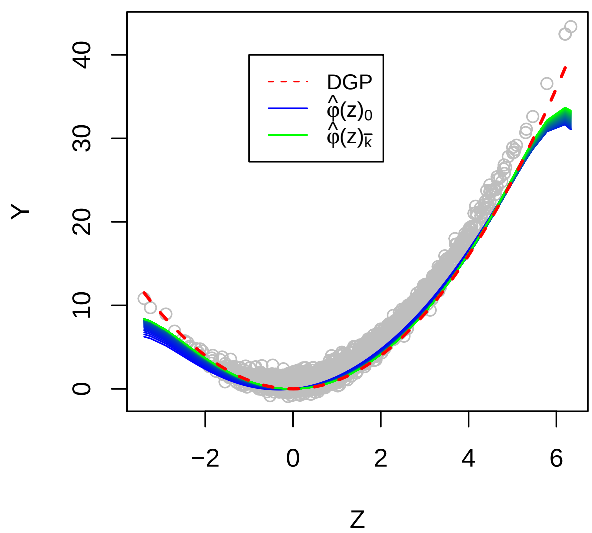

Figure 5.1: The regularized solution path of the proposed estimator

The number of iterations is determined by the stopping criterion given in (5.32). That is, if there is no significant change in the value of this criterion between two successive iterations, the iteration stops. Figure 5.3 shows the evolution of the value of the stopping criterion throughout the iterations. As illustrated, the criterion's value decreases from the

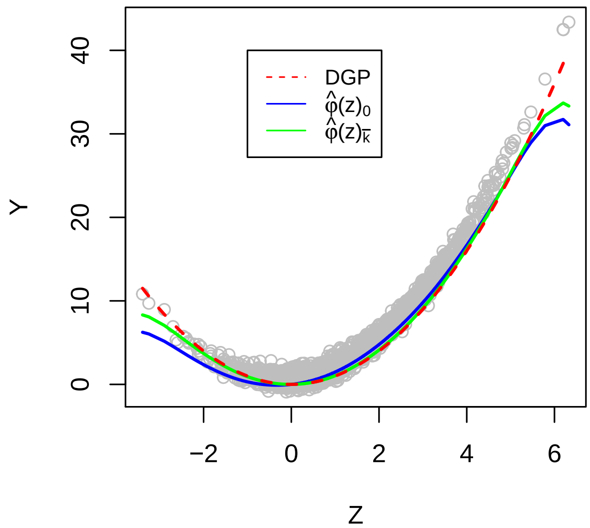

Figure 5.2: Comparison between the initial guess and the final IV regression estimate

first iteration on until it flattens out. I specify a tolerance level of 1%, meaning that if the stopping criterion's value between two iterations changes by 1% or less, the iteration procedure stops. This is here achieved after $\bar{k} = 44$ iterations. One could set a lower tolerance level to achieve a higher accuracy, which, however, also increases the computational burden. Note that another choice to make is for the constant $c < 1$, which is required for the convergence of the iterative scheme (see equation (5.31)). The higher the value of c, the faster the iterative scheme converges (Centorrino et al., 2017). I here fixed $c = 0.5$.[13]

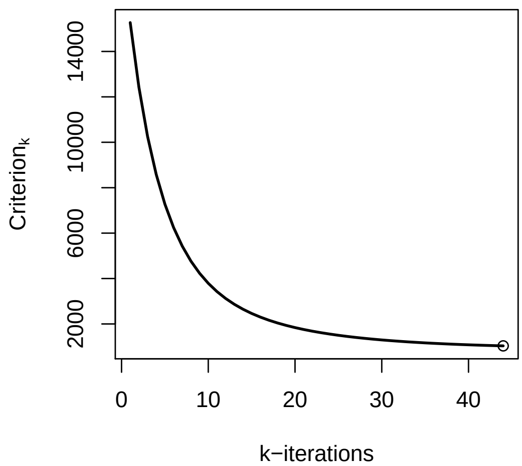

Figure 5.3: Stopping criterion

[13] Florens et al. (2018), for instance, also specify $c = 0.5$.

To illustrate possible biases I compare different nonparametric estimators, based on the described DGP. An overview of the compared estimators is presented in Table 5.2

Table 5.2: Description of the compared nonparametric estimators

Estimator	Description
LL	Local-linear kernel regression (nonparametric OLS)
LMU	Local-within (two-ways) FE estimator (Lee et al., 2019)
L-F	Landweber-Fridman regularization (IV)
L-F/LMU	Landweber-Fridman and local-within (IV and FE, Section 5.3)

In particular, I compare i) simple local-linear estimation (LL), where no source of endogeneity is taken into account at all; ii) the local-within FE estimator presented by Lee et al. (2019) (LMU), that is, only taking into account individual and temporal FE; iii) the Landweber-Fridman procedure (L-F), i.e. only applying nonparametric IV regression without taking into account FE; and iv) the here presented estimator, the Landweber-Fridman regularization in combination with the local-within estimator (L-F/LMU), i.e. nonparametric IV and FE regression; Figure 5.4 shows the results applying the different estimators. It can be seen that all estimators, except the L-F/LMU estimator, leads to biased estimates, as none of the corresponding estimated conditional means hits the true DGP, indicated by the dashed red line. As expected, the L-F/LMU estimator is closely located around the true curve, which suggests a good finite sample behavior.

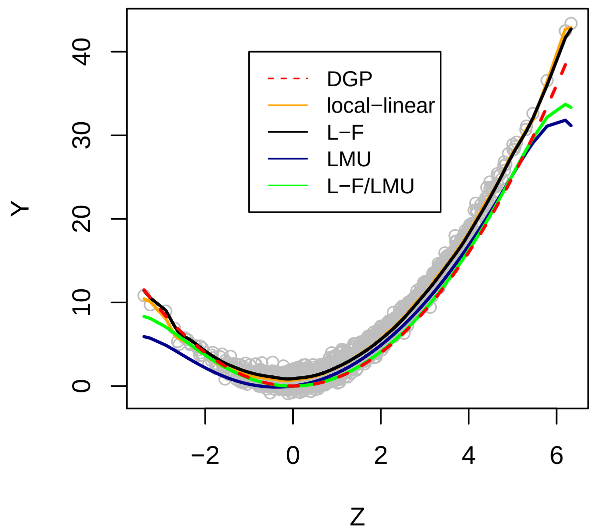

Figure 5.4: Comparison between nonparametric estimators

5.4.3 Finite sample behavior

To properly investigate the proposed estimator's finite sample performance, I conduct a Monte Carlo simulation using different sample sizes. In particular, building on the Monte Carlo simulation shown by Lee et al. (2019), I use four sets of samples of $n \in \{50, 100\}$ and $T \in \{10, 20\}$, each generated from the above described DGP. Then, $\varphi(Z_t)$ from (5.33) is estimated based on 400 random samples (for each of the four sets) using the estimators L-F/LMU, L-F, LMU, and LL (see Table 5.2 for a description of the estimators). Further, for each of the estimators, the Integrated Mean Squared Errors (IMSE) and the Integrated Mean Absolute Errors (IMAE) are computed by averaging pointwise MSE and MAE over z, where the RIMSE reports the root of IMSE. Typically, Monte Carlo simulations with nonparametric estimators are computational time intensive, not only because of pointwise estimation, but also because, ideally, optimal bandwidths should be used for each repetition. Beyond that, the nonparametric instrumental estimators, based on the Landweber-Fridman regularization method, need various iterations themselves to yield the final estimate. Unfortunately, the available computational power does not allow me do conduct the Monte Carlo simulation using optimal bandwidth for each of the repetitions. Instead, for each of the compared estimators and each of the four samples, I compute optimal bandwidths only for the first of the 400 repetitions and which will then be used for the remaining repetitions. This surely introduces some bias, especially at the boundaries of the data, but allows nonetheless to conjecture on the estimator's finite sample behavior.

Table 5.3 presents the results. For all datasets, the proposed L-F/LMU estimator, taking endogeneity in the explanatory variable and FE into account, reaches the lowest values both for the RIMSE and the IMAE, indicating the best estimation performance among the applied nonparametric estimators. Considering the RIMSE, it can be seen that increasing the sample size improves the here proposed L-F/LMU estimator's performance. Especially when increasing the time dimension from $T = 10$ to $T = 20$ leads to a significant improvement. The IMAE shows a similar pattern, where the best performance of the L-F/LMU estimator is shown for the largest dataset with $n = 100$ and $T = 20$, suggesting convergence and a good finite sample behavior of the estimator. Generally, the RIMSE is higher compared to the IMSE because the RIMSE squares the errors before averaging, which puts higher weights on large errors that occur particularly at the boundaries. This effect becomes amplified when not using optimal bandwidths for each of the 400 random samples. Hence, the IMAE might here be preferably considered to evaluate the estimators' performance. Among the other estimators, the LMU estimator shows the best performance, as it grasps a large part of the unobserved heterogeneity. Instead, the L-F estimator and the local-linear estimator do not show any significant improvement when increasing the sample size. It would be interesting to conduct the same simulation based on different DGP's to confirm and further study the performance of the estimator.

Table 5.3: Monte Carlo simulation: RIMSE and IMAE comparison

		RIMSE				IMAE			
n	T	L-F/LMU	L-F	LMU	LL	L-F/LMU	L-F	LMU	LL
50	10	1.041	1.664	1.501	1.793	0.350	1.606	0.781	1.675
50	20	0.309	1.660	0.894	1.797	0.123	1.604	0.760	1.678
100	10	0.822	1.670	1.258	1.778	0.250	1.609	0.865	1.660
100	20	0.524	1.663	0.915	1.786	0.116	1.608	0.717	1.668

Note: RIMSE is the Root Integrated Mean Squared Error and IMAE is the Integrated Mean Absolute Error of the estimators. The different estimators are applied to estimate $\varphi(Z_t)$ from equation (5.33), repeated 400 times for each dataset. See Table 5.2 for a description of the compared estimators.

5.5 Application to the estimation of the inverse demand function

To apply the proposed estimator on real data I estimate the inverse demand function, using U.S. data from Koebel and Laisney (2016). The following sub-sections present the inverse demand specification, the data, and the estimation results.

5.5.1 Inverse demand specification

The inverse demand function I aim to estimate is specified by

$$P_{it} = P(Q_{it}) \exp(\xi_i + \delta_t + U_{it}), \qquad i = 1, \dots, n \;\; t = 1, \dots, T \tag{5.40}$$

where P_{it} and Q_{it} denote the production price index and total production, respectively, for the i'th 2-digit industry at t. $P(\cdot)$ represents the inverse demand function, the function of interest to be estimated. ξ_i and δ_t are unobserved effects capturing industry specific characteristics as well as macroeconomic variables such as unemployment rate, GDP interest rate, etc., affecting all industries. Both ξ_i and δ_t are assumed to be potentially correlated with the explanatory variable Q_{it}. Taking the log of (5.40) yields the final regression model, given by

$$Y_{it} = \widetilde{P}(Z_{it}) + \xi_i + \delta_t + U_{it}, \tag{5.41}$$

where $Y_{it} \equiv \log P_{it}$ and $Z_{it} \equiv \log Q_{it}$.[14,15] Note that this specification slightly differs from the one presented in Koebel and Laisney (2016), since I presume separability of the function P from the error components ξ_i, δ_t, and U_{it}, which is necessary for the applicability of the

[14] An estimate of the inverse demand function $\widehat{P}$ can be recovered by $\widehat{P}(Q_{it}) = \exp\left(\widehat{\widetilde{P}}(Z_{it})\right)$.

[15] Note that the regression equation (5.41) is also interesting since the first derivative of $\widetilde{P}(Z_{it})$ directly yields the price elasticity w.r.t. output. That is,

$$\epsilon_{P|Q}(Z_{it}) = \widetilde{P}'(Z_{it}) = \frac{\partial P(Q_{it})}{\partial Q_{it}} \frac{Q_{it}}{P_{it}}.$$

proposed estimator. Instead, Koebel and Laisney (2016) model the inverse demand as a parametric exponential function, including the FE, i.e. $P(Q_{it}, \xi_i, \delta_t, U_{it})$. They take the FE into account by industry and time specific dummies and use nonlinear GMM to estimate the parameters of interest.

The inverse demand function presented in equation (5.40) is not distinguishable from the supply equation, which is likewise a function that maps industries' output level into prices. Since the equilibrium mechanism implies that the demanded production level is simultaneously determined with the price, it can then be shown that by construction, in equation (5.40), total production, Q_{it} is correlated with the error term, U_{it} (Wooldridge, 2016). Therefore, in order to identify the demand function $P(\cdot)$, we need not only to control for the FE but we also need an instrument such as an output supply shifter, i.e. variables only affecting the supply but not the demand. Possible output supply shifter are the prices for labor and materials, denoted by w^l_{it} and w^m_{it}, respectively, and hence candidate instruments. Empirically, to be valid instruments, they need to satisfy $cor(w^j_{it}, Q_{it}) \neq 0$ and $E(U_{it}|w^j_{it}) = 0$, with $j = \{l, m\}$. However, testing the instruments for validity is beyond the scope of this work and, hence, the here presented results need to be considered with caution.

5.5.2 Data

The data used in Koebel and Laisney (2016) is provided by the Bureau of Labor Statistics (BLS) and contains production and price data of 21 2-digit U.S. manufacturing industries ($n = 21$), covering the period 1949 to 2001 ($T = 53$). This yields a balanced panel of 1113 observations. Output is given in quantities and prices are represented by 2-digit price indices, normalized to one at the year 2000.[16] Table 5.4 provides some summary statistics of the concerned variables.

Table 5.4: Summary statistics

Variable	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Q_{it}	232.74	378.77	8.60	46.82	203.28	2,729.07
P_{it}	0.60	0.36	0.12	0.27	0.90	1.95
w^l_{it}	0.39	0.30	0.03	0.12	0.65	1.06
w^m_{it}	0.61	0.34	0.10	0.31	0.93	1.90

Note: The variables Q_{it}, P_{it}, w^l_{it}, and w^m_{it} denote industries' total production, output price index, labor price index, and materials price index.

[16]See Koebel and Laisney (2016) Appendix B for further details on the data.

5.5.3 Estimation results of the inverse demand function

Using labor prices as instrument

Consider first the estimation results using the industries' labour price index as instrument. Figure 5.5 shows the estimation results related to equation (5.41), i.e. the estimation of the inverse demand, where the different lines represent the regularized solution path, starting from the initial guess $\widehat{\widetilde{P}}(Z_{it})_0$ (represented by the blue line) until reaching the final IV regression estimate $\widehat{\widetilde{P}}(Z_{it})_{10}$ (represented by the green line). The figure shows that throughout the iterations the curve moves upwards, where the pointwise estimate of the inverse demand of the last iteration is for some regions very close to the zero line. Note that the minimum of the stopping criterion was reached after 10 iterations, illustrated in Figure 5.6. Figure 5.5 also shows that the estimation becomes very volatile where the density of the observations is scarce, which is typical for nonparametric estimation. It is important to mention, however, without confidence bounds, it is not possible to interpret these results reliably.

Figure 5.7 compares the estimations results using different estimation methods. In particular, I compare again the local-linear, the LMU, the L-F, and the here proposed LMU/L-F estimator (see Table 5.2 for a description of the compared estimators). Consider first the local-linear and the L-F estimates, represented by the yellow and black lines, respectively. Both curves seem to have the same tendencies: after a decrease for low (log) production levels the curves rise, whereupon they quite continuously increase (except a short decrease between the log production levels of 6 and 7). Note that, here neither individual nor time FE are taken into account. Instead, the estimates from the LMU and the L-F/LMU estimators, represented by the blue and green lines, show for different intervals opposite directs in terms of their slopes. The strongest negative relation between the log output price and log production is estimated for both curves between the log production level around 2.5 and 4 and between about 6.5 and 8. Generally, the estimation results show that prices do not always decrease in the production level which violates the law of demand. Also, this indicates that parametric models, such as the one used by Koebel and Laisney (2016), may suffer from misspecification.[17]

[17] Also see Appendix 5.8, showing the corresponding estimates for the inverse demand related to equation (5.40), i.e. the estimates from the log-log model transformed into exponential values.

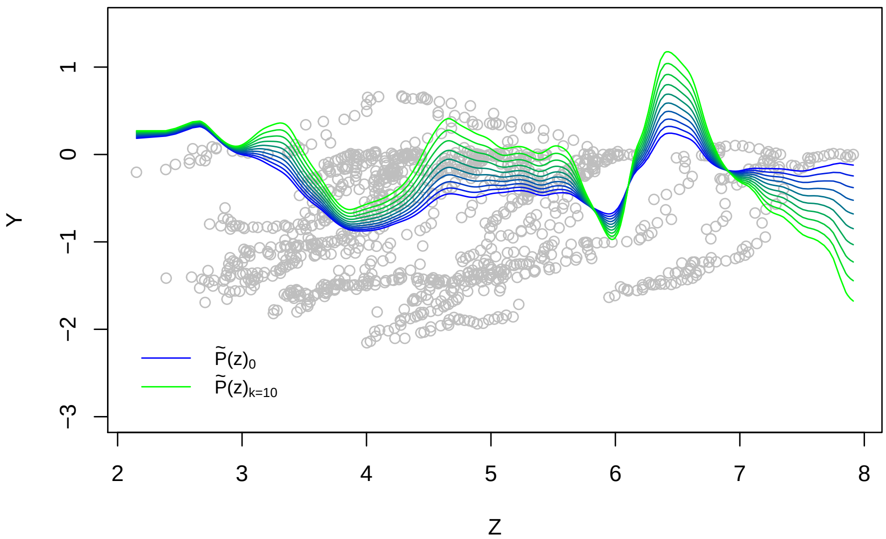

Figure 5.5: Estimation of the (log) inverse demand using labour prices as instrument

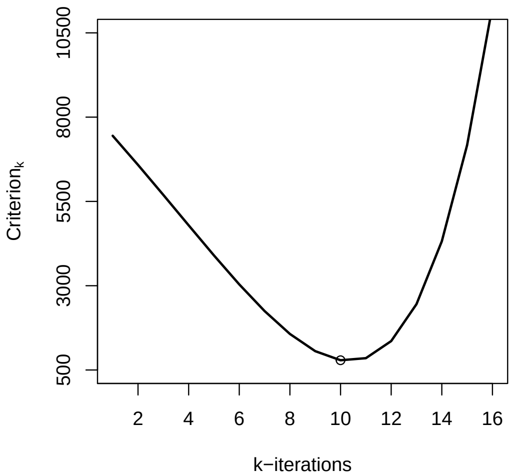

Figure 5.6: Stopping criterion using labor prices as instrument

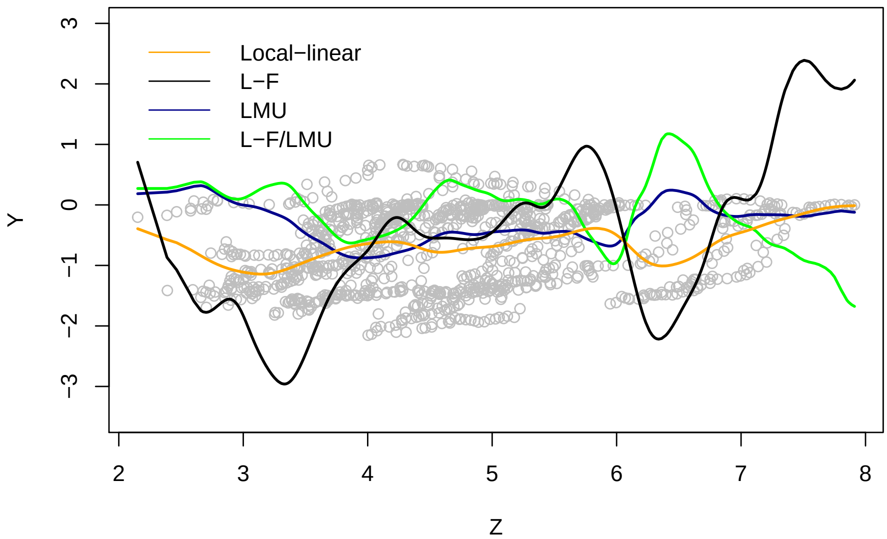

Figure 5.7: Comparison between nonparametric estimators using labour prices as instrument

Using material prices as instrument

Using material prices as instrument changes the estimates. Consider Figure 5.8, showing the regularized solution path of to obtain the estimated (log) inverse demand, where the upper blue and the lower green line represent the initial guess $\left(\widehat{\widehat{P}}(Z_{it})_0\right)$ and final estimate $\left(\widehat{\widehat{P}}(Z_{it})_7\right)$, respectively. Contrarily to the previous case, the curves shift downwards throughout the iterations, leading to a lower price level for a given level of output. In fact, the estimated average log price level is given by -1.58, which is considerably lower compared to the case when using labor prices as instrument, given by 0.081. Note that the minimum of the stopping criterion is reached here at the $7th$ iteration, shown in Figure 5.9. The differences in the estimates using different instruments also show that estimates react sensitively to the choice of the instrument, which is well-known for the parametric case (Donald and Newey, 2001; Kapetanios, 2006).

In order to compare the different estimators, as before, I consider the estimates for the inverse demand function, shown in Figure 5.10 (keeping the same colour convention as before). Note that the local-linear and the LMU estimates are not affected by the change in the instrument, since no instruments are used. The L-F estimates slightly change w.r.t. the case where labor price was used as instruments. The here proposed L-F/LMU estimator yields a strongly decreasing inverse demand up to the log production level of 4, whereupon an increase in the estimated curve is shown. That is, the price levels are decreasing for lower production levels but increasing for higher levels, which, here again, implies a violation of the law of demand.

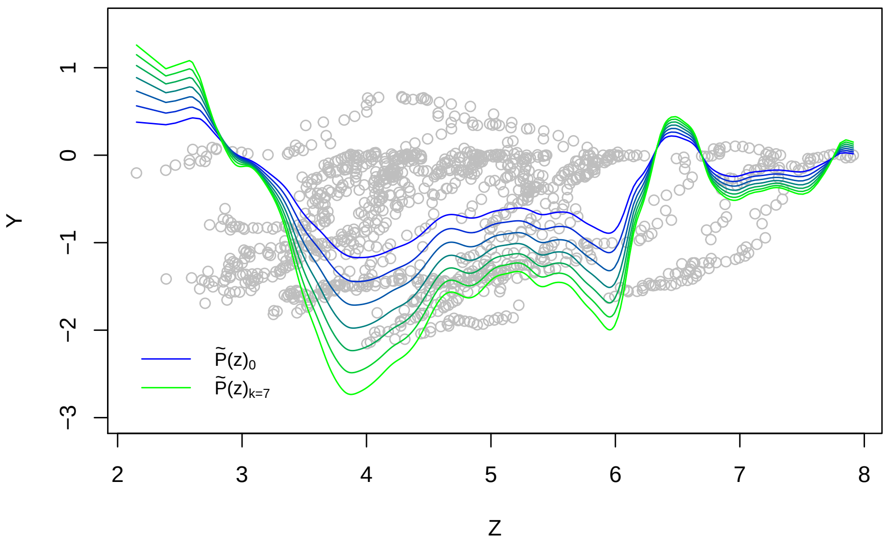

Figure 5.8: Estimation of the (log) inverse demand using material prices as instrument

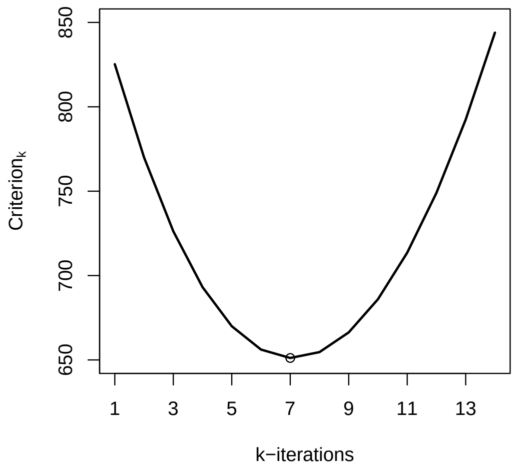

Figure 5.9: Stopping criterion using material prices as instrument

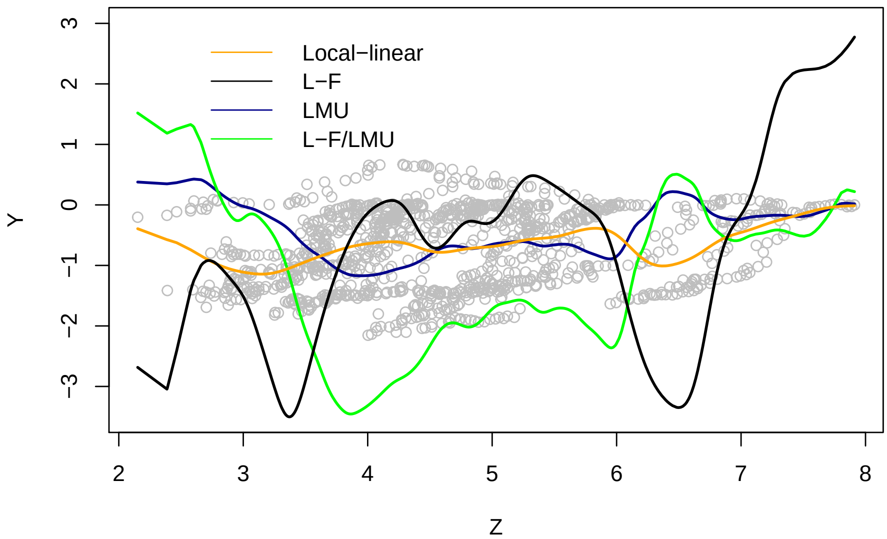

Figure 5.10: Comparison between nonparametric estimators using material prices as instrument

5.6 Conclusion

The chapter presents a nonparametric instrumental estimator for the conditional mean function, while taking into account (additive) fixed effects (FE). The estimator can be considered as an alternative to the one presented in Fève and Florens (2014) and is interesting for applied research with respect to its flexibility in treating different panel models with endogenous variables, that is, with either individual, time or two-way FE. This is achieved by using the Landweber-Fridman regularization method for the nonparametric IV part combined with the local-within FE estimator presented by Lee et al. (2019). The proposed estimator is applied on simulated data, where a Monte Carlo simulation shows good finite sample performance. Further, the estimator is applied to the special case of the estimation of the inverse demand function, relying on the model and data presented in Koebel and Laisney (2016). The results show that prices are not continuously decreasing in production levels, which violates the law of demand and which, therefore, indicates potential misspecification in the parametric model used by Koebel and Laisney (2016). Furthermore, the results reveal that the choice of the instrument matters. More precisely, in the case where material prices are used as instrument, the estimation leads to considerable lower price levels for a given level of output compared to the case where labor prices are used as instrument.

Yet, this approach does not comprise the estimation of corresponding confidence intervals for the provided point estimates. Hence, reliable interpretation of the results w.r.t. the estimation of the inverse demand is not possible. Moreover, similar to what is presented in Fève and Florens (2014), Florens et al. (2018) and Lee et al. (2019), the marginal effect (and higher order derivatives) of the conditional mean function, would be an important improvement. This would be useful and interesting in particular in the case of the estimation of the inverse demand, since the estimation of its first and second order derivatives would allow to nonparametrically test the Novshek condition for the existence of the Cournot equilibrium (Novshek, 1985).[18] Furthermore, it would be interesting to generalize the estimator to a dynamic panel model, including a lagged dependent variable, which is a frequently applied approach in panel data econometrics (see De Monte and Koebel (2021) for an example of a parametric linear dynamic panel model for the estimation of the inverse demand function).

[18] The Novshek condition is given by $P'(Y+y) + P''(Y+y)y \leq 0$, where P' and P'' denote the first and second derivative of the inverse demand function and $Y+y$ denotes the total output of all producing firms of a given industry with y the output of a specific firm.

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5.7 Appendix A: Bandwidth selection via leave-one-out cross-validation

Whenever the estimation procedure described in Section 5.3.2 uses the LMU estimator, optimal bandwidths should be computed applying least-squares leave-one-out cross-validation. As described in Section 5.2.2, the estimate of the conditional mean function $\widehat{\varphi}(z)$, is obtained upon a first-step estimate of the first gradient of $\widehat{\varphi}(z)$, denoted by $\widehat{\beta}_1(z)$. Henderson et al. (2015) point out that the optimal bandwidth for the estimation of the gradient(s), is not necessarily optimal for the estimation of the conditional mean and vice-versa. Therefore, while in Lee et al. (2019) a cross-validation procedure based on the gradient is described, I here propose to use a conditional mean based procedure. More precisely, the optimal bandwidth for the conditional mean, h_m^* estimate, in the case of an individual effect, is obtained by

$$h_m^* = \underset{h_m}{\operatorname{argmin}} \left(Y_{it} - \widehat{\varphi}_{-i}(Z_{it}, h_m)\right)$$

where $\widehat{\varphi}_{-i}$ is the leave-one-out estimate obtained based on the locally demeaned variables

$$Y^*_{-i,t}(Z_{it}) = Y_{it} - \frac{\sum_{j\neq i} K_h(Z_{jt} - z_{it})Y_{jt}}{\sum_{j\neq i} K_h(X_{jt} - x_{it})}, \quad Z^*_{-i,t}(z_{it}) = X_{it} - \frac{\sum_{j\neq i} K_h(Z_{jt} - z_{it})Z_{jt}}{\sum_{j\neq i} K_h(Z_{jt} - z_{it})}.$$

And analogously if $\widehat{\varphi}$ is aimed to be estimated in the framework of a panel model with temporal or two-ways fixed effects.

5.8 Appendix B: Estimation of the inverse demand

Figure 5.11 and 5.12 show the comparison of the estimation of inverse demand, referring to equation (5.40), using different estimators (see Table 5.2 for a description of the compared estimators). That is, the shown curves are simply obtained taking the corresponding exponential values of the log-log regression model, i.e. the dependent variable $\exp(Y_{it})$, and the obtained pointwise estimate of the elasticity, $\exp\left(\widehat{\widehat{P}}(Z_{it})\right)$.

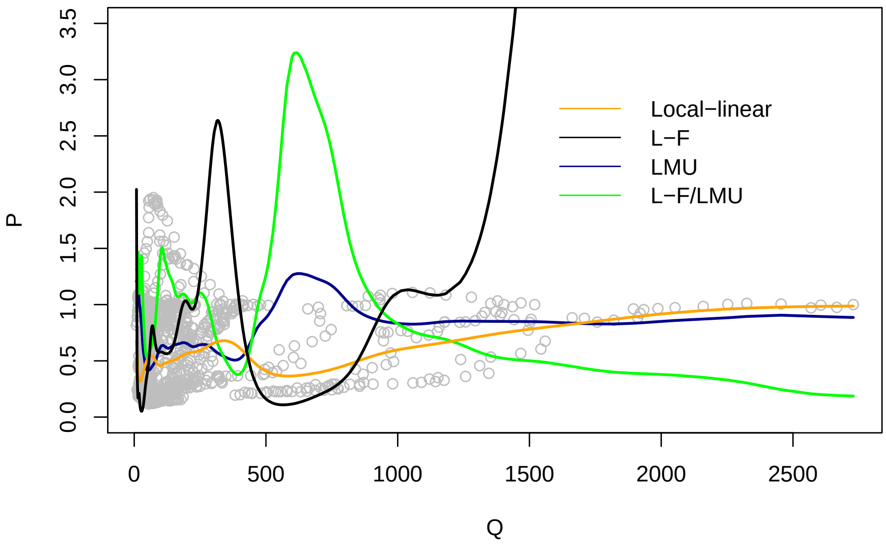

Figure 5.11: Inverse demand estimation, using labor prices as instrument

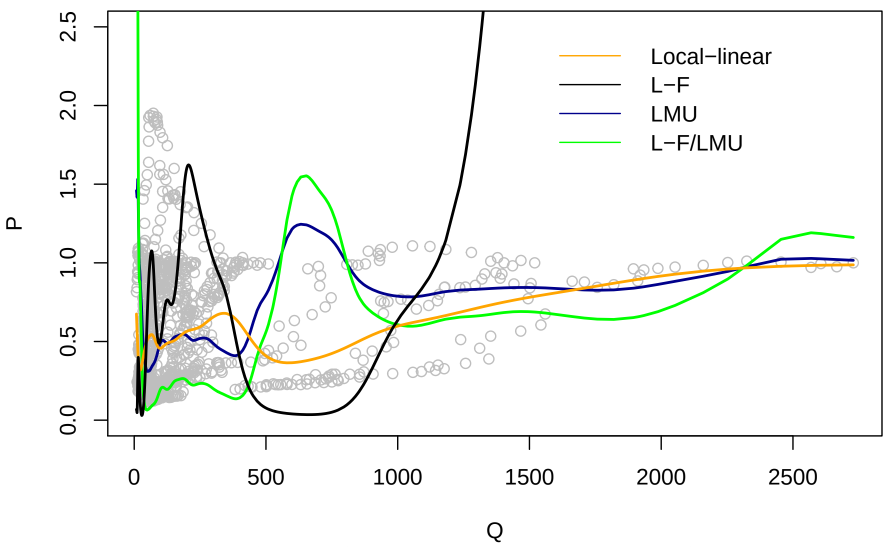

Figure 5.12: Inverse demand estimation, using material prices as instrument

Chapter 6

Conclusion

6.1 Summary of the dissertation

This thesis investigates productivity and markup dynamics as well as firm competition and welfare in the French manufacturing industry. For the empirical investigation, the thesis uses a large firm-level dataset covering the time horizon from 1994 to 2016, where productivity and markups are econometrically estimated by means of structural production models. The setup of a market equilibrium model allows to theoretically investigate firms' technology in terms of their cost-efficiency in fixed and variable costs as well as to derive new insights into welfare effects in a market with heterogeneous firms.

In particular, Chapter 2 investigates productivity dynamics of the French woodworking industry as a special case of the French manufacturing industry. The results show that aggregate productivity of the French woodworking industry grew considerably during the periods 1994-2000 and 2001-2007. During the period of the economic and financial crisis, 2008-2012, the industry's aggregate productivity growth experienced a significant slowdown, which recovered over the period 2012-2016. Generally, the most important driver for these productivity dynamics is shown to be the group of incumbent firms that contribute considerably more to aggregate productivity growth compared to the groups of firms that enter or exit the market. Further, the chapter investigates aggregate productivity growth w.r.t. firms' export status and shows that the aggregate productivity of the group of exporters grows more consistently during different periods compared to non-exporters and that exporting firms generally exhibit a higher productivity level. Investigating the contribution of firms' domestic and export economic activity to aggregate productivity growth shows that domestic activity is related to a decrease in aggregate productivity as the French woodworking industry generates by far most sales in the domestic market. The results therefore suggest that a more international orientation of the industry, both in terms of the number of exporters and in terms of export intensity, promises higher and more sustainable productivity growth.

Chapter 3 generalizes the analysis of the preceding chapter not only by considering the entire French manufacturing industry but also by estimating productivity using a less restrictive model. Along with the evolution of aggregate productivity, this chapter also measures the evolution of aggregate markups, by taking firm entry and exit into account. The results show that aggregate productivity in the French manufacturing industry has consistently grown throughout the period 1994-2016, where the growth was primarily driven by incumbent firms' productivity improvements rather than by firms' entry and exit. The results also show a slowdown in aggregate productivity growth, which is mainly induced by a slowed reallocation process of output shares among incumbent firms. The investigation of aggregate markups, as a proxy for the degree of market power in the French manufacturing industry, shows that aggregate markups remain relatively stable over time. Here, especially incumbent firms maintain a high level of markups, and, as a consequence, contribute positively to the aggregate markup evolution. By contrast, entering firms tend to have lower market power and/or adopt an aggressive price policy to remain in the market.

Chapter 4 explicitly models competition among firms à la Cournot, where heterogeneity in firms' technologies is taken into account by the introduction of firm specific fixed and variable costs, which is novel in the literature. The analysis of the model shows that the long-run Cournot equilibrium may be inefficient due to too many entries, which is similar to the case of homogeneous firms, and that higher industrial concentration of production is welfare-improving. The empirical investigation of the model shows the the importance of both observed and unobserved heterogeneity for explaining firms' cost and marginal revenues. Frequently, fixed costs are found to be very small, but significant for the smallest and largest firm sizes, which may have policy implications for increasing the survival probability of small firms and for reducing inefficiencies (or market power) of bigger firms.

Chapter 5 is closely related to the previous chapter in that it considers the econometric estimation of the inverse demand function that is part of the Cournot competition model. In particular, the chapter develops a nonparametric instrumental estimator for the estimation of the conditional mean function by controlling for unobserved fixed effects. In doing so, the chapter proposes a flexibly applicable nonparametric solution for different kinds of endogenous panel models, i.e. with individual, time or two-ways fixed effects effects, by combining existing nonparametric kernel regression methods. The simulation results suggest good finite sample behavior of the proposed estimator. The estimator is then applied on aggregate data of the U.S. manufacturing industry to estimate the inverse demand function. The results illustrate that the price level is not always decreasing in the aggregate production level, pointing to a violation of the law of demand and to potential misspecification in parametric models.

6.2 Limitations and extensions

In spite of their many virtues, the analyses performed in this thesis also contain a number of limitations, which are grouped and discussed in the following.

6.2.1 Estimating firm-level productivity

The productivity estimates presented in Chapter 2 and 3 are both based on a Hicks neutral production function. This specification implies no unobserved heterogeneity in output elasticities, and assumes constant output elasticity across firms (in the case of the Cobb-Douglas production function used in Chapter 2) or output elasticity only varies via changes in firms' input mix (in the case of the translog production function used in Chapter 3). In other words, firms' entire technological progress is comprised in the additive productivity term. There are various ways to introduce a more general production technology: For instance, by specifying a production technology where productivity in the production process does not only occur in the form of an additive term but is also related to the input factor labor, which is referred to as non-neutral or factor augmented production function (Chen, 2017). Another way to generalize the model would be to further relax assumptions made on the functional form of the production function, such as shown by Gandhi et al. (2020) and Demirer (2020), who use fully nonparametric methods to prevent issues related to model misspecification. Furthermore, the estimates of firm-level productivity are based on revenue (output) and expenditure (inputs) data, which is deflated by 2-digit price indices. That is, variations in prices between firms both w.r.t. output and inputs are not accounted for. If, however, price differences vary with firms' output and input choices, the estimated coefficients of the production function suffer from the output/input price bias. Foster et al. (2008), De Loecker et al. (2016), and Morlacco (2017) discuss this concern in detail and provide approaches to circumvent the output/input price bias. Yet another limit related to the use of firms' revenue data is that the resulting measure of firm productivity conflates price-setting effects with physical productivity. In other words, a firm might be considered productive either because it is indeed cost-effective or simply because it has significant market power. Here, too, the use of firm-level price indicators or physical output data could refine the study in this respect.

6.2.2 Measuring market entry and exit

Chapter 2 and 3 investigate the effect of firm entry and exit on aggregate productivity and markups. Here, the identification of firm entry and exit is only based on firm observations in the data, i.e. firm entry/exit is measured when a firm appears/disappears at some point in-/from the dataset. This is a very common approach in the literature as information on firms' exact legal status is typically not available (Blanchard et al., 2012, 2014). However, with this method it is not possible to unequivocally distinguish between firms' temporal inactivity, reporting errors, and the real opening or closure of a firm. For that reason, measured effects related to firm entry and exit might be biased to some extent. A possible solution for that concern would be to merge the used data from FICUS and FARE with data on firms' legal status and define entry and exit based on that information. For instance, for France data on all registered firm IDs is publicly available, containing information on the creation and cessation of any firm activity.[1]

6.2.3 Modeling firm competition à la Cournot

In Chapter 4, the adopted Cournot competition model to study heterogeneous firms' technology in fixed and variable costs as well as welfare effects is, in the presented form, a static model. That is, firms are assumed to only make myopic decisions w.r.t. their optimal production level by taking their technology and possible actions of their competitors into account. The extension towards a dynamic model would be the next natural step, where firms not only chose their optimal output quantity but also decide on their activity status (to continue or to shut down their business) by evaluating their firm value over (infinite) future periods. Well-known examples for such dynamic models are presented by Ericson and Pakes (1995) and Doraszelski and Satterthwaite (2010), which could be extended to the case of heterogeneity in firms' fixed and variable costs.

Furthermore, the econometric estimation of the presented Cournot model leaves room for improvement. In particular, the model does not yet allow to accurately predict the firm size distribution, where the main reason for the occurring discrepancy is that the presented model targets the cost and the marginal cost function, but not the production level of our firms. Improving the model by using a moment fitting or simulated maximum likelihood approach would here be helpful. A further reason for the gap between the predicted and the actual distribution of firm sizes is that the empirical model only includes two unobserved heterogeneity terms, which respectively affect the fixed cost and the first derivative of the cost function. A third unobserved heterogeneity term is actually required to allow for heterogeneous second order derivatives of the cost function w.r.t. production and which determines the optimal (and heterogeneous) firm size. Such extensions will be included in the future work.

6.2.4 Nonparametric estimation with endogenous variables

Regarding the nonparametric instrumental estimator with additive fixed effects, proposed in Chapter 5, an important improvement would be an extension to include the estimation

[1] Publicly available data of firms' legal status in France: https://www.sirene.fr/sirene/public/static/acces-donnees, (April, 2021).

of the first and higher order derivatives of the conditional mean function w.r.t. the explanatory variable. This would be both useful and interesting in particular in the case of the estimation of the inverse demand function, since the estimation of its first and second order derivatives would allow to nonparametrically test the Novshek condition for the existence of the Cournot equilibrium (Novshek, 1985). Furthermore, it may be interesting to generalize the proposed estimator of the conditional mean function to a dynamic panel model, including a lagged dependent variable, which is a frequently applied approach in panel data econometrics (see Chapter 4 for an example of a parametric linear dynamic panel model).

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