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Introduction (Version française)

Cette thèse est consacrée aux comportements d'échange et aux performances de portefeuille des investisseurs individuels. En France, les investisseurs individuels représentent, en juin 2012, 8,3% de la population française de plus de 15 ans. Cette proportion a diminué de 5% depuis décembre 2008.[1] De nombreuses questions ont été soulevées par les chercheurs concernant ces investisseurs non-professionnels : La gestion de leurs portefeuilles est-elle efficace ? Existe t-il un lien entre leurs caractéristiques individuelles et les rentabilités de leurs portefeuilles ? Leurs performances sont-elles persistantes dans le temps ? Investissent-ils comme des professionnels ?

Les études académiques démontrent que de nombreux investisseurs individuels prennent des décisions qui ne peuvent être réconciliées avec la théorie financière classique. Ces décisions sont généralement qualifiées de biais comportementaux (voir Barber et Odean (2013) pour une revue de la littérature sur le comportement des investisseurs individuels). Il est, par exemple, largement documenté que les investisseurs individuels sous-diversifient leurs portefeuilles, détenant en général moins de titres qu'il n'en faut pour annuler le risque spécifique (Kelly (1995) ; Kumar (2007) ; Goetzmann et Kumar (2008)). En outre, ils souffrent d'un biais de familiarité et

[1]Source : Les Echos/ TNS Sofres pour La Banque Postale

investissent dans des actions domestiques ou émises par leur employeur (Massa et Simonov (2006) ; Ivkovic et Weisbenner (2005)). Les études montrent également que les investisseurs individuels sont sujets à l'effet de disposition. Ils sont en effet plus prompts à réaliser leurs gains tandis qu'ils conservent leurs positions perdantes trop longtemps (Shefrin et Statman (1985) ; Weber et Camerer (1998) ; Odean (1998)). D'autres recherches mettent en évidence qu'ils favorisent l'achat de titres qui captent leur attention tels que les actions des entreprises médiatisées, les actions qui affichent des volumes d'échanges anormaux et celles dont le prix atteint un maximum historique (Seasholes et Wu (2007) ; Barber et Odean (2008)). Enfin, les investisseurs individuels semblent échanger trop fréquemment compte tenu de leurs compétences et de l'information qu'ils détiennent (Barber et Odean (2000) ; Odean (1999)). L'ensemble de ces travaux soulignent que les performances de nombreux investisseurs individuels sont pénalisées par des choix d'investissement sous-optimaux.

Les trois premiers chapitres de cette thèse sont consacrés à la performance de portefeuille détenus par les investisseurs individuels. Nous examinons leurs comportements de rachat dans le dernier chapitre. Nos recherches ont été menées sur une base de données de 85 400 investisseurs individuels français, soit plus de 8 millions de transactions réalisées entre 1999 et 2006. Un tableau récapitulatif des sous-échantillons utilisés dans chaque chapitre est présenté en annexe A.

Les recherches académiques montrent que les investisseurs individuels affichent de piètres performances de portefeuille. Dans son article pionnier "Do individual investors trade too much", Odean (1999) rapporte que les investisseurs individuels américains affichent des rentabilités négatives *avant* imputation des coûts de transactions. Cette observation amène l'auteur à tirer la conclusion que les investisseurs individuels échangent de façon excessive. Parallèlement, Barber et Odean (2000) mettent en évidence que les portefeuilles gérés par les investisseurs individuels sous-performent le marché en grande partie *à cause* des frais de transactions. Sur le marché finlandais, Grinblatt et Keloharju (2000) montrent que les investisseurs individuels achètent les titres qui réalisent de faibles performances dans le futur tandis que les investisseurs professionnels achètent les titres qui réalisent de fortes performances. Notons que les pertes agrégées des investisseurs individuels sont non-négligeables. Par exemple, sur le marché Taïwanais, elles représentent 2,2% du PIB (Barber, Lee, Liu, et Odean (2013)).

Ainsi, les investisseurs individuels gagneraient à confier la gestion de leur portefeuille à des investisseurs professionnels. Tout au moins, ils devraient investir dans l'indice de marché ou dans un fond mutuel. Une revue de littérature complémentaire sur les performances des investisseurs individuels est présentée en annexe B.1.

Les performances de portefeuille des investisseurs individuels ont été analysées dans de nombreux pays mais aucune recherche de ce type n'a été réalisée sur les investisseurs français. Le premier chapitre présenté dans cette thèse constitue la première étude dédiée aux performances de portefeuille des investisseurs individuels français.[2]

Notre étude se fonde sur 7 911 046 transactions réalisées par 56 723 investisseurs entre 1999 et 2006. Premièrement, nous démontrons que les investisseurs français,

[2]Ce chapitre correspond à un article à paraître dans *Bankers, Markets and Investors.*

comme leurs homologues étrangers, affichent des rentabilités ajustées au risque négatives. En moyenne le alpha de Jensen mensuel associé aux portefeuilles est de l'ordre de $-0,6\%$. Deuxièmement, les investisseurs les plus sophistiqués, pour lesquels nous pourrions attendre des performances supérieures, ne sur-performent pas leurs pairs. La sophistication est un déterminant important mais encore peu exploré des performances. Une discussion sur la sophistication est proposée dans le chapitre 4 et en annexe B.2. Dans ce premier chapitre, nous considérons qu'un investisseur est sophistiqué s'il échange des titres étrangers, s'il détient un portefeuille diversifié et s'il échange sur plusieurs types de comptes. Ce dernier indicateur est basé sur une spécificité française. Les investisseurs qui traitent sur deux types de comptes sont sophistiqués car ils prennent parti de la flexibilité d'un compte titres traditionnel et d'un compte exonéré d'impôts (*i.e.*, un PEA). Troisièmement, nous montrons que les titres achetés par les investisseurs sous-performent les titres vendus. Par exemple, sur un horizon de 3 mois (resp. 6 mois, 1 an), la différence de rentabilité moyenne entre les titres achetés et vendus est de -0,71% (resp. -1,13%, -1,79%). Si l'on considèrait en outre les coûts de transactions, les pertes seraient encore plus importantes. Cette dernière analyse de la profitabilité des échanges est réalisée sur la période 1999-2006 et sur trois sous-périodes : la bulle internet (1999-2000), la post-bulle internet (2001-2002) et la période haussière de 2003-2006. Nos résultats sont robustes, quelle que soit la tendance du marché. Enfin, un portefeuille *long-short* qui reproduit les décisions d'achat et de vente des investisseurs réalise un alpha mensuel moyen de -0,19% sur un horizon d'un mois.

Nous concluons que les investisseurs individuels français ne font pas exception à la règle et gagneraient à appliquer une stratégie passive.

Dans le second chapitre de cette thèse nous étudions l'influence des niveaux d'aspirations individuels sur les performances de portefeuille.[3] L'aspiration correspond à un niveau de richesse de référence à partir duquel l'investisseur détermine ses gains et ses pertes. Les analyses classiques mettent en évidence que l'hétérogénéité des performances est liée aux caractéristiques individuelles observables des investisseurs telles que les variables socio-démographiques (Barber et Odean (2000) ; Barber et Odean (2001) ; Korniotis et Kumar (2009a)), l'expérience (Nicolosi, Peng, et Zhu (2008)), ou l'intelligence (Grinblatt, Keloharju, et Linnainmaa (2011)). Ces études posent implicitement l'hypothèse que les investisseurs qui partagent les mêmes caractéristiques ont des préférences homogènes. Ces similitudes dans les préférences ont pour conséquence des comportements d'échanges similaires.[4] Dans ce chapitre, nous faisons l'hypothèse inverse et considérons que les investisseurs appartenant à une même catégorie socio-démographique peuvent avoir des aspirations latentes, et donc non observables, différentes.

Les niveaux d'aspiration constituent un aspect important de la prise de décisions, déjà étudié dans un contexte managérial (March et Shapira (1987) ; Mao (1970) ; Diecidue et Wakker (2001) ; Brown, De Giorgi, et Sim (2012)). Par une segmentation originale des investisseurs, nous montrons que différents niveaux d'aspiration conduisent à des décisions d'investissement différentes et par conséquent, à des perfor-

[3] Ce chapitre correspond à un article à paraître dans *Finance Research Letters.*

[4] Notre analyse sur l'impact de la sophistication dans le chapitre 1 est fondée sur la même hypothèse.

mances hétérogènes. Plus précisément, nous évaluons les aspirations des investisseurs selon la Théorie Comportementale du Portefeuille (TCP) développée par Shefrin et Statman (2000). Ce cadre représente un modèle alternatif à l'approche Moyenne-Variance de Markowitz (1952). La Théorie Comportementale du Portefeuille se fonde sur la Théorie SP/A de Lopes (1987)[5] et sur la Théorie des Perspectives de Kahneman et Tversky (1979) et Tversky et Kahneman (1992). [6]

Selon la Théorie Comportementale du Portefeuille, un investisseur cherche à maximiser sa richesse tout en satisfaisant le critère *Safety First* de Roy (1952). Pour vérifier cette contrainte, la probabilité que la richesse passe sous le niveau d'aspiration doit être inférieure à un seuil acceptable. Le niveau d'aspiration correspond ici à un niveau de richesse que l'investisseur espère atteindre. Il en résulte que le portefeuille optimal de la TCP n'est généralement pas efficient au sens Moyenne-Variance (Shefrin et Statman (2000)). En effet, les investisseurs considèrent leur portefeuille comme une pyramide d'actifs avec les instruments les moins risqués dans le bas de la pyramide et les instruments les plus risqués dans le haut, chaque couche étant associée à un niveau d'aspiration. Les couches inférieures répondent au besoin de sécurité et les couches supérieures permettent d'atteindre des rentabilités potentiellement larges.

[5]Dans la Théorie SP/A, trois facteurs doivent être pris en considération lors de la prise de décisions d'un investisseur : La sécurité (S), le potentiel (P) et l'aspiration (A). L'aspiration est liée à un objectif que l'investisseur souhaite atteindre. La sécurité et le Potentiel sont liés aux deux émotions principales qui opèrent sur les individus : la peur et l'espoir.

[6]Cette théorie est basée sur 4 propositions : (1) Les investisseurs utilisent des probabilités subjectives et sur-pondèrent la probabilité des évènements extrêmes (2) Les investisseurs déterminent la valeur subjective de chaque résultat à partir d'une fonction de valeur. L'utilité est dérivée des changements de richesse, relativement à un point de référence à partir duquel les gains et les pertes sont définies. La sensibilité relativement à ce point de référence est décroissante (3) Les investisseurs sont averses aux pertes (4) Les investisseurs sont averses au risque pour la plupart des gains et les pertes peu probables, et preneurs de risque pour la plupart des pertes et les gains peu probables.

En d'autres termes, les investisseurs divisent leur portefeuille en comptes mentaux, chacun étant dédié à un objectif (retraite, dépense d'éducation, etc.) et caractérisé par un niveau d'aspiration. Lorsqu'ils créent leurs portefeuilles les investisseurs de la TCP procèdent en deux étapes. Ils satisfont d'abord le critère *Safety first* et sécurisent leur niveau d'aspiration le plus faible. Ensuite la richesse restante est investie dans des actifs ayant le potentiel pour atteindre des niveaux d'aspirations plus élevés.[7]

Dans notre étude empirique réalisée sur 26 166 investisseurs individuels entre 1999 et 2006, nous comparons les performances de portefeuille d'investisseurs ayant des niveaux d'aspirations faibles et élevés. Nous identifions deux profils opposés en fonction des titres qu'ils échangent. Les investisseurs qui ont de fortes aspirations échangent plus fréquemment et détiennent des portefeuilles plus risqués. En revanche, les investisseurs ayant de faibles aspirations diversifient plus et détiennent des portefeuilles moins risqués. Ces caractéristiques sont cohérentes avec les résultats de Hoffmann, Shefrin, et Pennings (2010). Ces auteurs croisent les données mensuelles d'un questionnaire adressé aux clients d'un courtier avec le registre de leurs transactions. Ils montrent que les investisseurs motivés par des objectifs de spéculation ont des aspirations supérieures, échangent plus fréquemment, prennent plus de risques et se jugent plus compétents par rapport aux investisseurs motivés par le besoin de se constituer un matelas de sécurité, ou d'épargner pour leur retraite.

Nous montrons que les investisseurs qui ont des aspirations élevées (faibles) sous-performent (sur-performent) leurs pairs. Le alpha de Jensen mensuel pour les investisseurs ayant de fortes aspirations s'élève à -0,7293 en moyenne, comparé à -0,3818

[7]Notons que deux cas peuvent être considérés pour la TCP : Un seul compte mental et de multiples comptes mentaux. Dans cette étude, nous faisons référence à la version à plusieurs comptes mentaux.

pour les investisseurs ayant de faibles aspirations. Notre principale contribution est de montrer que ces résultats ne sont pas déterminés par les facteurs classiques de performance tels que la fréquence des échanges, le niveau de diversification et les facteurs de risque. En effet, nos résultats sont robustes lorsque l'on contrôle pour ces effets. Nous montrons que les aspirations individuelles latentes constituent des variables clés pour expliquer les différences observées dans les performances de portefeuille des investisseurs.

Dans le troisième chapitre de cette thèse, nous abordons la question de la performance de portefeuille par le biais de la mesure d'évaluation choisie.[8] Plus précisément, nous examinons l'importance du choix de la mesure de performance dans l'évaluation des portefeuilles des investisseurs individuels.

La question de l'importance du choix de la mesure de performance a déjà été évoquée dans la littérature. D'une part, Eling et Schuhmacher (2007) comparent 13 mesures de performance[9] par l'évaluation de 2 763 hedge funds entre 1985 et 2004. Les auteurs montrent que toutes les mesures de performance affichent une corrélation très élevée avec le ratio de Sharpe, variant entre 0,93 et 1. Eling et Schuhmacher (2007) concluent que les mesures alternatives de performance produisent toutes le même classement de fonds que le ratio de Sharpe. Eling (2008) corrobore ces résultats avec une analyse de 38 954 fonds mutuels. Selon ces articles, l'utilisation systématique du

[8] Ce chapitre correspond à un article qui a reçu le prix du meilleur papier de doctorant lors de la 5ème conférence annuelle de l'Académie de Finance Comportementale, Chicago, 2013.

[9] Alpha de Jensen, ratio de Sharpe, ratio de Treynor, ratio Omega, ratio de Sortino, ratio Kappa 3, ratio Upside Potential, ratio de Calmar, ratio de Sterling, ratio de Burke, rentabilité anormale sur Value at Risk, ratio de Sharpe conditionnel, ratio de Sharpe modifié

ratio de sharpe est ainsi justifiée.

D'autre part, Zakamouline (2011) explique que les observations de Eling et Schuhmacher (2007) et Eling (2008) sont biaisées, de par la méthodologie employée et les mesures de performance seléctionnées. A partir d'arguments théoriques et d'autres mesures alternatives, Zakamouline (2011) conclut que le choix de la mesure de performance est importante pour l'évaluation des fonds.

Quelques travaux sont ainsi dédiés au rôle de la mesure de performance pour l'évaluation des fonds mais aucune étude similaire n'a été réalisée sur les investisseurs individuels. Nous réalisons la première étude consacrée au choix de la mesure de performance dans l'évaluation des performances de portefeuille des investisseurs individuels. Etant donné le consensus qualifiant les investisseurs individuels de piètres gestionnaires de portefeuille, cette question est fondamentale. En effet, l'évaluation des portefeuilles est toujours réalisée avec les mesures classiques que sont le alpha de Jensen, la constante de Fama-French ou encore le ratio de Sharpe. Dans ces mesures, le risque est évalué par la variance des rentabilités, qui alloue un poids similaire aux déviations positives et négatives des rentabilités par rapport à la rentabilité moyenne. Cependant les investisseurs semblent favoriser les mesures de risque asymétriques capable de capturer principalement les pertes (Veld et Veld-Merkoulova (2008)). À partir d'un questionnaire, Veld et Veld-Merkoulova (2008) montrent également que les investisseurs qui détiennent principalement des actions évaluent le risque selon la semi-variance, tandis que les investisseurs qui détiennent principalement des obligations évaluent le risque selon la probabilité de pertes.

Dans ce troisième chapitre nous choisissons le ratio de Sharpe comme mesure de performance de référence et considérons cinq mesures alternatives qui répondent aux faiblesses mentionnées ci-dessus. La structure de ces mesures permet de mesurer le risque à partir des déviations négatives des rentabilités par rapport à une rentabilité cible (*i.e.*, downside risk). De plus, les mesures alternatives intègrent différentes hypothèses sur les préférences des agents. Une première mesure traduit des préférences neutres face au risque. Une seconde intègre l'aversion aux pertes à travers une surpondèration pour les pertes. Une troisième mesure est cohérente avec la Théorie de l'Utilité Espérée. Dans cette théorie, les investisseurs affichent une attitude uniforme envers le risque. Alternativement à la Théorie de l'Utilité Espérée, Kahneman et Tversky (1979) proposent une fonction de valeur conforme aux comportements qu'ils ont observé expérimentalement : aversion au risque pour les gains et recherche de risque pour les pertes. Une quatrième mesure est choisie pour prendre en considération ces préférences. Enfin, une cinquième mesure retenue répond à la Théorie Comportementale du Portefeuille de Shefrin et Statman (2000). Ce modèle intègre la préférence des investisseurs pour des titres ayant les caractéristiques d'une loterie et la recherche de skewness à travers leurs transactions (Conine et Tamarkin (1981) ; Mitton et Vorkink (2007)).

Ce chapitre met en exergue plusieurs résultats originaux. Premièrement, nous montrons que le choix de la mesure de performance influence fortement l'évaluation des portefeuilles des investisseurs individuels. Par exemple en 2003, la proportion d'investisseurs qui sont sur-classés (sous-classés) avec une mesure alternative au ratio de Sharpe s'étend de 35,94% à 46,45% (de 5,85% à 36,19%). Deuxièmement, si l'on compare la performance relative du portefeuille des investisseurs par rapport à l'indice de marché, les investisseurs individuels ne sont pas de si mauvais gestionnaires. Par exemple en 2006, seuls 10% des investisseurs battent le marché selon le ratio de Sharpe. Cette proportion s'élève à 60% lorsque l'on se base sur la mesure cohérente avec la Théorie Comportementale du Portefeuille. Avec cette mesure, 30% des investisseurs sur-performent le marché pendant 4 années consécutives, tandis qu'aucun ne bat le marché de manière persistante avec le ratio de Sharpe. Enfin, nous créons aléatoirement des portefeuilles sous-diversifiés reproduisant la structure des portefeuilles détenus. Le poids alloué à chaque action est déterminé par un processus aléatoire. Ces portefeuilles sur-performent ceux détenus par les investisseurs, même avec les mesures alternatives. Ainsi l'amélioration des performances des investisseurs ne semble pas déterminée par leurs compétences en terme de sélection de titres mais par des effets mécaniques liés à la sous-diversification de leurs portefeuilles. Par conséquent, bien que l'importance du choix de la mesure de performance constitue notre résultat principal, nous ne pouvons conclure que les investisseurs individuels affichent une expertise particulière pour sélectionner les actions qu'ils introduisent dans leur portefeuille.

Le dernier chapitre de cette thèse est consacré aux comportements de rachat par les investisseurs individuels. De nombreux articles s'intéressent aux décisions d'achat et de vente de titres par les investisseurs individuels (voir Barber et Odean (2013)), mais les préférences de rachat de titres par ces agents ont été beaucoup moins étudiées. Récemment, Strahilevitz, Odean, et Barber (2011) ont mis en évidence deux schémas de sélection sur une base de données américaine. En moyenne, les investisseurs préfèrent (1) racheter les titres qu'ils ont vendu pour un profit (2) racheter les titres qui ont perdu de la valeur depuis la vente. Ces résultats corroborent les observations expérimentales de Weber et Welfens (2011). Si l'on considère le premier comportement, Nofsinger et Varma (2013) montrent que la récence des ventes de titres joue un rôle important dans les comportements de rachat, qui domine l'impact de la profitabilité antérieure. Selon cet auteur, la décision de rachat pour un titre dépend donc principalement du *timing* des échanges.

Strahilevitz, Odean, et Barber (2011) suggèrent que ces préférences sont motivées par les réactions émotionnelles des investisseurs suite à leurs échanges. Plus précisément, les investisseurs tentent d'éviter de ressentir des émotions négatives telles que le regret (Zeelenberg, Beattie, Van Der Pligt, et De Vries (1996)). Le regret est généralement provoqué par des pensées contrefactuelles, *i.e.*, des scénarios alternatifs qui auraient abouti à de meilleurs résultats (Roese (1997)). L'importance de ce sentiment dans les décisions de rachat est largement documentée en marketing. Par exemple, Tsiros (1998) met en évidence que le regret expérimenté peut conduire à un changement de marque même si les consommateurs sont satisfaits de la marque achetée. De la même façon, l'anticipation du regret influence également les choix (Zeelenberg, Beattie, Van Der Pligt, et De Vries (1996)). En effet, les consommateurs produisent fréquemment des pensées préfactuelles lorqu'ils considèrent un achat (McConnell, Niedermeierand, Leibold, El-Alayli, Chin, et Kuiper (2000)).

Dans le contexte des comportements de rachat de titres, le regret expérimenté se manifeste comme suit. Un investisseur dont la vente d'une action engendre une moins-value regrette d'avoir acheté cette action. Par conséquent, il tend à choisir d'autres titres dans ses échanges futurs. Parallèlement, l'anticipation du regret se manifeste lorsque le prix d'une action a augmenté depuis que l'investisseur l'a vendue. Ce dernier sait qu'il aurait pu gagner davantage en retardant sa vente. Il anticipe que le rachat du titre va intensifier ce regret et préfère alors ignorer ce titre.[10]

Ce dernier chapitre constitue la plus importante étude dédiée aux comportements de rachat des investisseurs individuels dans un contexte européen. Nous analysons les transactions de 34 129 investisseurs entre 1999 et 2006 et corroborons les résultats de Strahilevitz, Odean, et Barber (2011). Premièrement, les investisseurs sont plus enclins à racheter des actions dont la vente a permis la réalisation d'un gain plutôt que celles dont la vente a donné lieu à une perte. Deuxièmement, ils sont plus enclins à racheter un titre dont le prix a diminué depuis la vente plutôt qu'un titre dont le prix a augmenté depuis la vente. Sur la base d'une analyse de survie, nous montrons que si une plus-value est réalisée lors de la vente, la durée moyenne entre la vente et un rachat est de 52,6 jours, contre 54,7 jours pour un titre vendu pour une perte. Le temps moyen de rachat d'un titre dont le prix a baissé depuis la vente est 49 jours, contre 60 jours pour un titre dont le prix a augmenté depuis la vente.

Contrairement aux travaux existants, notre principale contribution est d'analyser ces comportements au niveau individuel. En effet, la méthodologie employée par Strahilevitz, Odean, et Barber (2011) est pertinente au niveau agrégé mais n'est pas optimale au niveau individuel. Nous mettons en lumière l'hétérogénéité des comportements individuels. Plus précisément, nous évaluons comment les attributs individuels, tels que la sophistication, influencent les comportements de rachat.

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[10]Il faut noter que le regret anticipé a été modelisé dans la Théorie du Regret par Loomes et Sugden (1982)

La sophistication d'un investisseur correspond au degré de connaissance et d'expertise des marchés financiers et des instruments d'investissement. Elle peut être estimée par des variables socio-démographiques telles que la richesse, l'âge ou l'éducation (Dhar et Zhu (2006) ; Goetzmann et Kumar (2008) ; Calvet, Campbell, et Sodini (2009)). Des mesures d'intelligence et de capacités cognitives sont également utilisées pour détecter les investisseurs sophistiqués (Christelis, Jappelli, et Padula (2010) ; Grinblatt, Keloharju, et Linnainmaa (2011)). La sophistication peut être observée, sur la base d'indicateurs tels que l'échange de produits complexes, le recours aux ventes à découvert ou le niveau de diversification (Feng et Seasholes (2005) ; Goetzmann et Kumar (2008) ; Korniotis et Kumar (2013)). Enfin, la sophistication est parfois évaluée sur la base de questionnaires (Van Rooij, Lusardi, et Alessie (2011) ; Kimball et Shumway (2010)). Une revue de littérature complémentaire sur la sophistication des investisseurs est présentée en annexe B.2.

Dans ce chapitre, nous évaluons le degré de sophistication des investisseurs selon trois mesures directes : le niveau de diversification, la propension à traiter des actions étrangères et le nombre de comptes détenus pour placer des ordres. Nous montrons que les investisseurs sophistiqués sont moins sujets aux comportements de rachat décrits. Par exemple, un investisseur qui échange sur deux types de comptes et a vendu un titre pour un gain a moins tendance à racheter cette action qu'un investisseur qui n'échange pas sur deux types de comptes. Un investisseur qui est classé dans le meilleur quintile de diversification et qui a vendu un titre dont le prix a diminué depuis la vente est moins enclin à racheter cette action qu'un investisseur qui détient un portefeuille moins diversifié.

Dans la dernière partie de ce chapitre nous testons si des explications alternatives permettent de mieux appréhender ces comportements. Nous montrons que les préférences de rachat ne sont pas motivées par la détention d'informations privées ou une expertise particulière. En effet, les titres rachetés sont moins rentables que les titres vendus ou achetés par les investisseurs. Par exemple, sur un horizon de 3 mois la rentabilité moyenne des titres rachetés est de 0,34%, contre 0,82% pour les titres achetés et 1.30% pour les titres vendus. En outre, les performances de portefeuille des investisseurs qui affichent les comportements de rachat décrits ne sont pas plus élevées que celles de leurs pairs. Nous montrons enfin qu'une stratégie contrariante n'est pas capable d'expliquer la préférence pour le rachat de titres dont le prix a baissé depuis la vente. Ainsi, les motivations rationnelles ne permettent pas d'expliquer les préférences de rachat.

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Introduction

This dissertation investigates the trading behavior and performance of individual investors. In France in June 2012, 8.3% of French people over the age of fifteen were individual investors. This proportion had decreased since December 2008, when it corresponded to 13.8% of the population.[11] Researchers have raised many questions about these non-professional investors: Is their portfolio management effective? Are their preferences and trading decisions beneficial? Is there any link between individual characteristics and portfolio returns? Are their performances systematic? Do they trade like professionals?

Academic studies report that many investors invest in ways that are hard to reconcile with standard financial theory and are therefore labelled as investment mistakes (see Barber and Odean (2013) for a review of individual investor trading behavior). For instance, it is widely documented that individual investors underdiversify their portfolios, generally holding much less stocks than usually recommended to cancel specific risk (Kelly, 1995; Kumar, 2007; Goetzmann and Kumar, 2008). These investors suffer from the familiarity bias, investing in local stocks or in their own company's stocks (Massa and Simonov, 2006; Ivkovic and Weisbenner, 2005). Studies also report

[11]Source: Les Echos/ TNS Sofres for La Banque Postale

that they are prone to the disposition effect. Indeed, they realize their gains whereas they keep their losing investments too long (Shefrin and Statman, 1985; Weber and Camerer, 1998; Odean, 1998). Another stream of research evidences that they favor attention-grabbing stocks such as headline stocks, stocks experiencing high abnormal trading volume, and stocks that are attaining historical price limits (Seasholes and Wu, 2007; Barber and Odean, 2008). Finally, individual investors seem to overtrade (Barber and Odean, 2000; Odean, 1999). Consequently, many investors hurt their performance by trading in suboptimal ways.

The three first chapters of this dissertation are dedicated to the trading performance of individual investors. We examine their repurchase behavior in the last chapter. Our research has been conducted using a database of 85,400 French individual investors who realized more than 8 million trades between 1999 and 2006. A table summarizing the subsamples used in each chapter can be found in Appendix A.

A general consensus in the literature is that individual investors exhibit poor portfolio performance. Odean (1999) shows that U.S. individual investors earn negative returns *before* transaction costs. This observation leads him to the conclusion that investors trade too much. In their seminal paper "Trading is hazardous to your wealth", Barber and Odean (2000) provide compelling evidence that self-managed portfolios underperform the market largely because of trading costs. On the Finnish market, Grinblatt and Keloharju (2000) find that individual investors are net buyers of stocks with weak future performance, while professional investors are net buyers of stocks with strong future performance. The aggregate trading losses of individual investors are substantial, as illustrated on the Taiwanese market where they represent 2.2% of Taiwan's total GDP (Barber, Lee, Liu, and Odean, 2013). As a result, individual investors would gain more from entrusting the management of their wealth to professional investors. They should at least invest in the market index or in a mutual fund. A complementary review of literature on trading performance of individual investors is presented in Appendix B.1.

Although the portfolio performance of individual investors has been analyzed in many countries, no previous literature describes the performance of French investors. The first chapter of this dissertation provides the first study available to date regarding the portfolio performance of French individual investors between 1999 and 2006.[12] Our empirical study is based on a sample of 7,911,046 transactions realized by 56,723 investors and contains several empirical results. Firstly, French investors portfolios are no exception to the rule as they exhibit negative risk-adjusted returns. The average investor earns a significant monthly Jensen alpha of -0.6%. Secondly, we focus on an important but little-explored determinant of performance: investors' sophistication[13]. We consider investors to be sophisticated if they trade foreign assets, hold a diversified portfolio (compared to the average diversification in the sample) and hold multiple accounts to place trade (the last indicator mentioned is based on a specific French taxation feature). Investors trading on two types of accounts are sophisticated because they take advantage of flexible traditional accounts and tax-free accounts. Although

[12] This chapter refers to the forthcoming article in *Bankers, Markets and Investors.*

[13] Sophistication is discussed in the presentation of chapter 4

we could expect noticeable results, most sophisticated investors fail to outperform their peers. In a third step, we examine the profitability of investors' trades and find that the stocks that are bought underperform the stocks that are sold. On a 3-month (resp. 6 months, 1 year) horizon, the average return difference between stocks purchased and sold is -0.71% (resp. -1.13%, -1.79%). Considering the transaction costs, we would expect shortfalls to be even greater. This analysis is carried out throughout the entire period (1999-2006) and for three specific sup-periods in our dataset: the internet bubble (1999-2000), the post-internet bubble (2001-2002) and the 2003-2006 bullish period. Similar patterns are observed, whatever the market trend. Lastly, we show that long-short portfolios mimicking the buy-sell trades of individual investors earn a reliably negative monthly alpha of 0.19% on a 1-month horizon.

Consistently with existing results, we conclude that French individual investors would gain more from applying a *buy and hold* strategy.

The second chapter of this dissertation studies whether individual aspirations can explain the observed heterogeneity in portfolio performance.[14] General evidence in the literature shows that cross-sectional variations in performance can be traced to observable characteristics of investors such as socio-demographic variables (Barber and Odean, 2000, 2001; Korniotis and Kumar, 2009a), experience (Nicolosi, Peng, and Zhu, 2008) or intelligence (Grinblatt, Keloharju, and Linnainmaa, 2011). The implicit assumption in all these studies is that investors who share the same char-

[14] This chapter refers to the forthcoming article in *Finance Research Letters*.

acteristics have homogenous preferences. It follows that these preferences result in similar trading behaviors. [15]

In this chapter, we assume that investors in the same socio-demographic group can differ by their latent, and thus not directly observable, aspirations. Aspiration level is a relevant aspect of decision making. For instance in a managerial context, March and Shapira (1987) show that the dangers of falling below the performance target dominate the attention of managers and affect executive decisions. This evidence is consistent with Mao (1970)'s conclusions, who find that managers define risk as what might happen if the return is lower than the target. Some theoretical studies also consider aspiration levels as part of the decision-making process (Diecidue and Wakker, 2001; Brown, De Giorgi, and Sim, 2012).

Our study is the first to segment investors according to their personal goals and show that different levels of aspiration lead to different investing decisions, resulting in heterogeneous portfolio performance. More precisely, we evaluate investors aspirations according to the Behavioral Portfolio Theory (BPT) developed by Shefrin and Statman (2000). This framework is an alternative model to the Mean-Variance approach developed by Markowitz (1952). BPT is drawn on the SP/A Theory of Lopes (1987)[16] and on the Prospect Theory of Kahneman and Tversky (1979) and Tversky and Kahneman (1992).[17] The Behavioral Portfolio Theory suggests that an

[15] Our own analysis of the impact of sophistication in chapter 1 is based on the same hypothesis.

[16] In SP/A theory, three factors have to be taken into consideration by the investor before making a choice: security (S), potential (P) and aspiration (A). Aspiration (A) relates to a goal investors want to reach. Security and potential relate to the main emotions that operate on individuals: fear and hope.

[17] This theory is based on 4 propositions: (1) Investors use subjective probabilities and overweight the probability of extreme events (2) Investors determine the subjective value of each outcome via a

investor chooses a portfolio that maximizes his behavioral expected wealth and meets safety first criterion (Roy, 1952). Satisfying the safety first constraint means that the probability for wealth to fall below an aspiration level is lower than an acceptable threshold. The aspiration level in BPT corresponds to a wealth level that the investors expect to reach. The main result of this model is that the optimal portfolio of a BPT investor is generally not mean-variance efficient. Indeed, investors do not simply allocate their wealth by minimizing the risk of the portfolio for a given level of expected return. Instead, they consider their portfolio as a pyramid of assets where the riskless instruments are at the bottom and the riskier ones are at the top, and each layer is associated with an aspiration level. The bottom layer addresses the desire for security and the top layer includes the riskier assets that have the potential for larger returns. In other words, investors divide their overall portfolios into mental account sub-portfolios where each mental account is devoted to a goal (retirement income, education expenses, bequests, etc.) and characterized by an aspiration level. To set their portfolio, investors proceed in two steps. First they satisfy the safety first criterion at the cheapest price; in other words, they secure their lowest aspiration level. The remaining wealth is then invested in instruments that generate payoff satisfying higher aspiration levels.[18]

In our empirical study conducted on 26,166 investors between 1999 and 2006, we compare the portfolio performance of investors with high and low aspiration lev-

value function. Utility is derived from changes in wealth, relative to a reference point with respect to which gains and losses are defined. The sensitivity decreases in relation to this reference point (3) Investors are loss averse (4) Investors are risk averse for most gains and unlikely losses, and are risk seeking for most losses and unlikely gains

[18]Two cases for BPT can be considered: one single mental account and multiple mental accounts. In this study, we refer to the multiple mental accounts version.

els. Based on the security they trade, we identify two opposed profiles. Those who have high aspirations trade more frequently and hold riskier portfolios. By contrast, investors who have low aspirations are more diversified and hold less risky portfolios. These characteristics are consistent with the findings of Hoffmann, Shefrin, and Pennings (2010). The authors match monthly survey data of brokerage clients with transaction records, and report that investors driven by objectives of speculation have higher aspirations and turnover, take more risks and consider themselves to be more advanced than investors driven by the need to build a financial buffer or save for retirement. We show that investors who have low (high) aspirations outperform (underperform) their peers. For instance, the monthly Jensen alpha computed for the average high aspiration investor is -0.7293, compared to -0.3818 for the average low aspiration investor. Our main contribution is that these findings are not driven by classic performance determinants such as trading frequency, diversification levels and risk factors. Indeed, even after controlling for these effects, our results remain constant. We thus provide evidence that latent individual aspiration is a key variable in explaining the highlighted cross-sections in the portfolio performance of investors.

In the third chapter of this dissertation, we tackle the portfolio performance issue from the measure perspective.[19] More precisely, we examine the importance of choosing the right performance measure to evaluate individual investors portfolios. A current research stream is attempting to establish whether the choice of performance measure influences the evaluation of risky portfolios. On the one hand, Eling and

[19] This chapter refers to the article which received the Best Doctoral Paper Awards in the 5th Academy of Behavioral Finance Conference, Chicago, 2013

Schuhmacher (2007) compare 13 measures of performance[20] through the evaluation of 2,763 hedge funds between 1985 and 2004. The authors show that all performance measures display a very high rank correlation with respect to the Sharpe ratio, as well as in relation to each other. The rank correlation coefficient for the Sharpe ratio varies between 0.93 and 1.00. Eling and Schuhmacher (2007) conclude that (p.4): *Despite significant deviations of hedge fund returns from a normal distribution, our comparison of the Sharpe ratio to other measures results in virtually identical rank ordering across the hedge funds.* Eling (2008) corroborates this observation with an analysis of the performance of 38,954 mutual funds. According to these articles, the systematic use of the Sharpe ratio is justified. On the other hand, Zakamouline (2011) argues that the results of Eling and Schuhmacher (2007) and Eling (2008) are biased due to the methodology employed and the performance measures selected. Based on theoretical arguments and alternative measures, Zakamouline (2011) concludes that the choice of performance measure is relevant to the evaluation of hedge funds.

Hence, although some studies are dedicated to the role of the performance measure in the evaluation of funds, no such work has been carried out on individual investors. Our work enriches existing literature with the first study to examine the choice of measure to evaluate the performance of individual investors portfolios. Considering the global evidence that individual investors are poor portfolio managers, this issue is of fundamental importance. Indeed, the evaluation of portfolios is always carried out using classic measures (Jensen's alpha, Fama-French intercept, Sharpe ratio). In these

[20] Jensen alpha, Sharpe ratio, Treynor ratio, Omega ratio, Sortino ratio, Kappa 3 ratio, Upside Potential ratio, Calmar ratio, Sterling ratio, Burke ratio, Excess return on value at risk (VaR), Conditional Sharpe ratio, Modified Sharpe ratio

measures, the risk associated with a choice is evaluated by the variance of returns. Yet the variance, which allocates the same weight to positive and negative deviations from the average return, does not reflect the way in which investors perceive risks. Instead, investors favor asymmetric risk measures which capture the concept of losses based on a benchmark return (Veld and Veld-Merkoulova, 2008). Based on a survey, Veld and Veld-Merkoulova (2008) report that investors who mainly hold stocks evaluate the risk according to semi-variance, whereas investors who mainly hold bonds evaluate the risk according the probability of losses.

In this chapter we focus on the Sharpe ratio as a benchmark performance measure and consider five alternative ratios which address the weaknesses described above. In these measures, risk is defined as negative deviations from a benchmark (i.e. downside risk). Moreover, alternative measures fit different preferences regarding gains and losses. A first measure conveys neutral preferences towards risk. A second one integrates the concept of loss aversion (i.e., losses loom larger than gains) through a higher weight for losses. A third measure is designed to be consistent with the standard Expected Utility Theory. In their alternative to the Expected Utility Theory, Kahneman and Tversky (1979) integrated the S-shaped Value function within the Prospect Theory. The Value function is consistent with experimental observations that investors are risk averse for gains and risk seeking for losses. A fourth measure is then designed to take this model of preferences into account. Finally, a fifth alternative measure in this study is consistent with the Behavioral Portfolio Theory of Shefrin and Statman (2000). The Behavioral Portfolio model integrates investors' preference for lottery payoffs and skewness seeking (Conine and Tamarkin, 1981; Mitton and Vorkink, 2007).

This third chapter presents several empirical results. First we show that the choice of performance measure strongly influences the evaluation of individual investors. In 2003, for example, the proportion of investors who are upgraded (downgraded) with an alternative measure to the Sharpe ratio ranges from 35.94% to 46.45% (5.85% to 36.19%). These proportions significantly differ from what is expected with random permutations. Our second observation is that individual investors are not such poor managers as reported by the Sharpe ratio ranking when they are compared to the market index. For example, although only 10% of investors in 2006 outperform the market index according to the Sharpe ratio, 60% of the population beat the market when evaluated with the measure fitting the Behavioral Portfolio Theory. With this measure, 30% of investors outperform the market for 4 consecutive years, whereas no investor beat the market persistently when evaluated with the Sharpe ratio. Finally we create under-diversified portfolios with randomly selected stocks. The weight allocated to each stock also results from a random process. These portfolios outperform those of investors in our sample, even with the alternative measures. The improvement of investors' performance is not therefore driven by their stock-picking skills but rather by mechanical effects linked to the skewness of their portfolio as a whole. As a result, though our main finding is the importance of the choice of measure, we do not conclude that individual investors exhibit particular skills to select outperforming stocks.

The last chapter of this dissertation is dedicated to the repurchase behaviors of individual investors. Many papers examine the buy and sell decisions of individual investors (see Barber and Odean (2013)) but much less is known regarding their repurchase preferences. Recently, Strahilevitz, Odean, and Barber (2011) evidenced two patterns of repurchase selection on a U.S. database. They show that on average, investors prefer to (1) repurchase stocks they had previously sold for a gain, (2) repurchase stocks that have lost value since being sold. These findings corroborate the experimental results of Weber and Welfens (2011). Regarding the first pattern, Nofsinger and Varma (2013) find that the recency of stock sales plays a major role in repurchasing behavior, which in turn dominates the impact of prior profitability. The authors show that the decision to repurchase a stock appears to be mostly dependent on the timing of trades of other stocks.

Strahilevitz, Odean, and Barber (2011) suggest that the repurchase preferences are driven by the investors emotional reactions to trading. More precisely, the authors argue that investors tend to avoid negative emotions such as regret. Regret is experienced when the outcome of a decision is unfavorable. Since unfavorable outcomes result in an unpleasant feeling, agents tend to make regret-minimizing choices (Zeelenberg, Beattie, Van Der Pligt, and De Vries, 1996). The importance of regret in repurchase decisions is widely documented in marketing research. Roese (1997) explains that regret is generally induced by counterfactual thinking, i.e., alternative scenarios that would have produced a better outcome ("If I had chosen that brand, I would have experienced more satisfaction than I do"). Tsiros (1998) evidence that experiencing regret may lead to brand switching even when consumers are satisfied with the purchased brand. The anticipation of regret also influences choices (Zeelenberg, Beattie, Van Der Pligt, and De Vries, 1996). Indeed, McConnell, Niedermeierand, Leibold, El-Alayli, Chin, and Kuiper (2000) shows that consumers frequently produce upward prefactuals (”if I buy it today and find it for less next week, I'll regret my purchase”) when considering a purchase. The effect of anticipating and experiencing regret during stock repurchase behaviors can be described as follows: An investor whose sale results in a loss experiences regret from purchasing the stock because its performance failed to meet expectations. As a result, the investor tends to select other stocks in future trades. Along the same lines, the anticipation of regret is likely to occur when a stock price has increased since the previous sale. The investor knows that a better outcome could have been obtained by selling later. Anticipating that the feeling of regret will intensify on repurchasing the stock, the investor therefore prefers to ignore this stock.[21]

The fourth chapter of this dissertation is the largest study to date that focuses on the repurchase behavior of individual investors in a European context. We analyze the trading records of 34,129 investors between 1999 and 2006 and corroborate Strahilevitz, Odean, and Barber (2011)'s findings. French investors also exhibit the two previously documented repurchase preferences. They are more prone to repurchasing stocks that they previously sold for a gain than they are to repurchasing stocks that they previously sold at a loss. They are also more prone to repurchasing stocks that have lost value than they are to repurchasing those that have gained value since the prior sale. We show that if a stock is sold at a profit, the average duration between the sale and a repurchase is 52.6 days, compared to 54.7 days if a stock is sold

[21]Note that anticipated regret has been modeled in Regret Theory by Loomes and Sugden (1982)

at a loss. The average time before the repurchase of stocks whose prices had declined since the sale is 49 days, compared to 60 days for stocks whose prices had increased since the sale. In contrast to previous works, our main contribution is to evidence the repurchase behavior at the level of each individual. Although the methodology employed by Strahilevitz, Odean, and Barber (2011) is reliable at an aggregate level (for the representative investor), it is biased at the individual level. We overcome this weakness using survival analysis techniques, thus making it possible to consider the existing heterogeneity in behaviors. More precisely we evaluate how individual attributes such as sophistication impact repurchase behavior.
Sophistication corresponds to the degree of knowledge and expertise in financial markets and investment instruments. This information can be estimated through socio-demographic variables including wealth, education or age (Dhar and Zhu, 2006; Goetzmann and Kumar, 2008; Calvet, Campbell, and Sodini, 2009). Metrics of intelligence and cognitive capacities are also used to detect sophisticated investors (Christelis, Jappelli, and Padula, 2010; Grinblatt, Keloharju, and Linnainmaa, 2011). Sophistication can be directly observed on the basis of indicators such as the trading of complex products, short-selling or diversification level (Feng and Seasholes, 2005; Goetzmann and Kumar, 2008; Korniotis and Kumar, 2013). Finally, sophistication is sometimes evaluated through surveys (Van Rooij, Lusardi, and Alessie, 2011; Kimball and Shumway, 2010). A summary of sophistication measures is presented in Appendix B.2.

In accordance with existing literature, we evaluate the investors degree of sophistication according to direct variables: their diversification level, their propensity to trade foreign stocks and the number of accounts they hold to place orders. Sophisticated investors suffer much less from repurchase preferences. For instance, an investor who trades on two accounts and has sold a stock at a profit is less inclined to repurchase this stock than an investor who does not trade on multiple accounts. An investor who is sorted in the top diversification quintile and has sold a stock which has decreased in price since the previous sale is less inclined to repurchase this stock than an investor who is less diversified. We next examine several factors that could motivate such behavior, and show that repurchase patterns are not motivated by private information or the trading skills of investors. Firstly, the repurchased stocks are less profitable than the stocks bought and sold during the same period. On a 3-month horizon, the average return of stocks repurchased by investors who suffer from the documented preferences is 0.34%, compared to 0.82% for the stocks purchased and 1.30% for the stocks sold. Secondly, the portfolio performance of investors who exhibit the repurchase preferences is not higher than that of their peers. This result corroborates our previous conclusion. The contrarian strategy also fails to explain investor preference for repurchasing stocks whose prices have declined since the previous sale. In fact, regarding their purchases, investors are more prone to selecting stocks whose price has recently increased. Rational motives do not therefore motivate these behaviors.

Based on empirical analyses, this dissertation thus contributes to a better understanding of the trading performance of individual investors and their trading behavior.

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Chapter 1

The trading performance of French retail investors

Forthcoming in *Bankers, Markets and Investors*

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Abstract

Based on more than 7 million transactions, we examine the financial performance of 56,723 French individual investors between 1999 and 2006. We show that French investors exhibit negative risk-adjusted returns on their portfolios and would be better off applying a *buy and hold* strategy. Most skilled investors, from whom we could expect noticeable results, do not perform better. Shortfalls can be explained by investors poor stock selection abilities. Indeed, the stocks they buy underperform the stocks they sell. This observation is robust for various market trends.

1.1 Introduction

A large body of empirical research indicates that the average individual investor underperforms the market and loses money by trading. For example, in a sample of 66,465 U.S. households from 1991 to 1996, the average investor earned an annual return of 16.4% while the market return was 17.9% (Barber and Odean, 2000). Grinblatt and Keloharju (2000) show that Finnish retail investors exhibited negative average performances between 1994 and 1996. Barber, Lee, Liu, and Odean (2009) document that the aggregate trading losses of individual investors are considerable; in the Taiwanese market, for instance, they are worth 32 billion, which is 2.2% of Taiwans GDP.

Investors poor performance can be traced to detrimental behaviors. Individual investors have a strong preference for selling stocks that have increased in value since the purchase date relative to stocks that have decreased in value since the purchase date (Shefrin and Statman, 1985; Shapira and Venezia, 2001; Seru, Shumway, and Stoffman, 2010). In the same vein, they have a tendency to be contrarians, i.e., buying past losers and selling past winners (Grinblatt and Keloharju, 2000). It is also widely documented that individual investors hold portfolios that are under-diversified (Kelly, 1995; Mitton and Vorkink, 2007; Goetzmann and Kumar, 2008) and overweight on familiar stocks (Huberman, 2001; Ivkovic and Weisbenner, 2005; Massa and Simonov, 2006; Seasholes and Zhu, 2010). Linnainmaa (2010) argues that many penalizing trading patterns can be explained in large part by investors use of limit orders. Another explanation lies in investors excessive trading frequencies (Barber and Odean, 2000; Odean, 1999). The role of transaction costs in the shortfall is directly linked to overtrading. Yet, individual investors seem to earn negative returns even before considering transaction costs. To summarize, quoting Barber and Odean (2013) (p.1565), investors "*trade frequently and have perverse stock selection ability, incurring unnecessary investment costs and return losses.*"

The financial performance of individuals has been studied in a number of countries, but no such research has been carried out in France. By investigating the performance of 56,723 individual French investors between 1999 and 2006, this paper fills that gap in the existing literature.

The global evidence that individuals lose money on their trades obscures considerable heterogeneity in investor profiles. Actually, researchers show that socio-demographic variables (Barber and Odean, 2000, 2001; Korniotis and Kumar, 2009a) and cognitive capacities (Seru, Shumway, and Stoffman, 2010; Grinblatt, Keloharju, and Linnainmaa, 2012) are able to explain the cross-sectional variation in performance. In contrast with those studies, we rely on direct proxies for sophistication to examine whether sophisticated investors exhibit greater success than their peers in portfolio management. Although the influence of sophistication on behavioral biases has been widely documented, less is known about the performance of sophisticated investors.

This work provides the most comprehensive study of the financial performance of French individual investors between 1999 and 2006. We first show that French investors are no exception to the rule, as they too exhibit poor performance. Their portfolio gross return and risk-adjusted return are indeed negative. Furthermore, we find that sophisticated investors, from whom we could expect noticeable results, do not perform better. Second, an analysis of the profitability of trading activity by French investors is provided, making use of the period particularity of our database. Indeed, the data run from 1999 to 2006, thus including the dotcom bubble, the post dotcom bubble, and the 2003 to 2006 trend of market growth. We provide the first evidence that French individual investors would be better off applying a passive strategy. More precisely, we show that the stocks they buy underperform the stocks they sell. Interestingly, this poor stock selection is observed under each market trend. We thus corroborate Hoffmann, Post, and Pennings (2013), who examine the impact of the 2008-crisis on individual investors behaviors. The authors show that investors do indeed continue to trade actively and do not de-risk their investment portfolios during the crisis.

This paper is organized as follows. Data are briefly presented in section 2.1, which is mainly dedicated to the portfolio performance of French investors. We examine the profitability of their trades in section 2.2 and conclude in section 3.

1.2 Empirical study

1.2.1 Portfolio performance of French individual investors

The main data set is provided by a large French online brokerage house. We obtained the daily transactions records for 56,723 French retail investors for the period from January 1999 to December 2006 for a total of 7,911,046 trades with 4,152,312 buy orders and 3,758,734 sell orders. Table 1.1 (Panels A and B) describes some preliminary statistics for the monthly trading activity of investors in our sample. Each month, the average amount purchased (sold) by investors corresponds to 19.77% (19.19%) of their portfolio value. Panel C is dedicated to portfolios. On average, the investors in our sample hold 6.2 stocks in their portfolio, with a median of 4.3 stocks. The average portfolio value is 26,256 euros (median 8,852 euros). Among the 56,723 investors of our dataset, 80.3% are men.

At first, a mean of 96 monthly returns is calculated for each investor. Monthly returns are computed based on daily returns. All returns are gross of transaction costs. The average return across investors is equal to -0.24% per month, i.e., -2.84% annualized. This average obscures considerable cross-sectional variations across households. Indeed, 46.84% of investors exhibit a negative average monthly return, and 42,275 investors underperform a value-weighted index.[1] The highest mean monthly return is 98.21%, whereas the lowest return is -64.21%.

Next, we compute 2 time-series of average returns across investors. In the first case, the averages constituting the time-series are computed with an equal weight of individual investors

$$Average\,Monthly\,Return = \frac{1}{N}\sum_{i=1}^{N} Monthly\,Return_{i,t} \tag{1.1}$$

[1]Data on the market index are given by the Eurofidai general index (computed using the methodology of the Center for Research in Security Prices, CRSP, and based on approximately 700 stocks over the period under consideration).

where i denotes the investor, t denotes the month, and N denotes the number of investors. In the second case, each investor is weighted using the investors monthly portfolio value $PV_{i,t}$ (based on portfolio values at the beginning of each month) to compute the time-series. This value-weighted average allows an aggregate level analysis.

$$Aggregate\,Monthly\,Return = \frac{1}{\sum PV_{i,t}} \sum_{i=1}^{N} Monthly\,Return_{i,t} * PV_{i,t} \tag{1.2}$$

Based on those time-series, we calculate two measures of risk-adjusted performance. We start with an estimation of the CAPM model by regressing the monthly excess return earned by individual investors (on average and in aggregate) on the market excess return. Then, we employ the three-factor model developed by Fama and French (1993). In both cases, we compute ordinary least squares (OLS)-estimated alphas, factor loadings and residuals.

$$Rp_t - rf_t = \alpha_p + \beta_p(Rm_t - rf_t) + \epsilon_t \tag{1.3}$$

$$Rp_t - rf_t = \alpha_p + \beta_p(Rm_t - rf_t) + z_pSMB_t + h_pHML_t + \epsilon_t \tag{1.4}$$

where Rp_t is the average (aggregate) monthly return of investors, Rm_t is the monthly return on a market index, β_p is the market beta and rf_t is the monthly risk free rate (1-month Euribor). Variable ϵ_t is the regression error term. In equation 1.4, SMB_t is the monthly return on a value-weighted portfolio of small stocks minus the monthly return on a value-weighted portfolio of large stocks, and HML_t is the monthly return on a value-weighted portfolio of high book-to-market stocks minus the monthly return on a value-weighted portfolio of low book-to-market stocks. Coefficients z_p and h_p are related to size and book to market factors.[2] Note that the Breusch-Pagan test and White general test do not detect heteroskedasticity.

The results relative to the regressions of monthly returns are reported in table 1.2.[3] First, even when the results are not significantly different from zero, all intercept estimations are negative, confirming existing results that individual investors (on average and in aggregate) do not outperform the market index. For example, in aggregate, the $CAPM-\alpha$ is equal to -0.52% (t=-1.7) and the Fama-French intercept is -0.86% (t=-2.7). Second, the betas are greater than one, indicating that investor portfolios bear a higher risk than the market as a whole. Indeed, on average, the coefficient estimates on the market excess returns are 1.33 and 1.44 for the CAPM and for the three-factor model, respectively. Third, the coefficient estimates on the factor of size are reliably positive, proving that individual investors tilt their portfolio toward small stocks. This result is in line with Barber and Odean's (2000)

[2] SMB_t and HML_t factors are provided by Eurofidai (www.eurofidai.org) and calculated according to the Fama and French (1993) methodology. The size factor (SMB) is formed annually and is obtained as follows. Each year firms are sorted based on the market capitalization at the end of the preceding year. Using the median of market capitalizations, the sample is divided into two classes of firm size. Furthermore, each year, firms are sorted by the book-to-market available at the end of the current year and the sample is split into three terciles. To construct the SMB factor, six value-weighted portfolios are used. The portfolios are the intersections of two portfolios based on size and three portfolios based on book-to-market. The return of the SMB factor is the equally-weighted average return on the three small capitalization portfolios minus the average return on the three big capitalization portfolios. The book-to-market factor (HML) is formed in the same way as SMB factor. Only the definition of the final portfolio differs. The return of the HML factor is the equally-weighted average return on the two Value portfolios minus the average return on the two Growth portfolios.

[3] Another common measure to evaluate portfolio performance is the Sharpe ratio (the mean excess return divided by its standard deviation). On average (in aggregate), the Sharpe ratio of investors is 0.19 (0.22). The Sharpe ratio for the market during our sample period is 0.50.

observation for American individual investors. At the same time, the coefficient estimates on book-to-market values are negative but not significant. Concerning the investors preference for small capitalizations, between 1999 and 2006, small capitalizations outperformed large capitalizations by 0.99% per month on average. For 40 months out of 96, they underperformed large capitalizations. Therefore, the preference for small stocks helped improve investor performance during our sample period.[4]

The robustness of our results is tested with a bootstrap on investors. More precisely, we create 1,000 subsamples of 5,000 investors selected randomly. For each subset, two 96-month time-series of average returns are computed following the same methodology than the one applied on the whole sample. CAPM and Fama-French intercepts are then estimated to obtain distributions of 5,000 alphas. On average, the $CAPM - \alpha$ (3-factor intercept) ranges between -0.64% and -0.58% (-0.92% and -0.84%) at the 95% confidence level. In aggregate, the $CAPM - \alpha$ (3-factor intercept) ranges between -0.63% and -0.40% (-1.03% and -0.70%) at the 95% confidence level. The estimations of intercepts on the whole dataset are included in these confidence intervals. Consequently, they are not likely to arise due to luck.

We mentioned that the performance of the average individual obscures a large heterogeneity. Researchers demonstrate that the cross-sectional variation in performance can be traced to cognitive abilities, location, and gender. We focus on investors sophistication and examine whether more sophisticated investors perform better than the

[4]Our findings on negative excess returns are not affected by the inclusion of a momentum factor in the regression (Carhart, 1997). Results are available upon request.

average. We postulate that sophisticated investors are likely to be skilled in gathering and interpreting information. In addition, we claim that sophistication is correlated with a better understanding of stock investments. Based on the prior assumptions, financial expertise should improve investors performance. We follow Boolell-Gunesh, Broihanne, and Merli (2012) and consider investors to be sophisticated if they trade foreign assets and hold multiple accounts to place orders. An additional variable to detect sophisticated investors is diversification (Feng and Seasholes, 2005). We thus create a dummy that takes the value of 1 if the average diversification of the investor is above the median value computed across all investors.[5]

First, we suppose that investors who trade foreign assets are sophisticated because they are more likely to be conscious of diversification benefits. Those investors do prove to be more diversified than their peers who do not trade foreign assets. In fact, the average number of stocks in their portfolios is 7.1 (median 5.1), compared to 4.1 (median 3.1) for investors who hold only French stocks. Second, holding multiple accounts to place trades is a measure based on a specific French taxation feature. Investors trading on the two types of accounts are sophisticated because they take advantage of the flexibility of a traditional account and the tax exoneration of a tax-free account, i.e., a PEA.[6]

Hence, investors are segmented according to the following variables: *Foreign as-*

[5]Diversification is computed as the number of stocks in a portfolio at the start of each month. As reported in table the median number of stocks is 4.3 stocks.

[6]With a PEA, investors are limited to eligible stocks and to eligible funds. The eligible stocks are those from any company headquartered in the European Union, Iceland or Norway. At least 75% of the eligible funds must be invested in the eligible stocks.

sets=1; Foreign assets=0; Two accounts=1; Two accounts =0; Diversification=1; and Diversification=0.

In the sample, 69.1% of investors trade foreign assets, 46.1% trade on 2 types of accounts and 50% of investors are diversified (i.e., they are sorted in the above median diversification group). Although Pearsons Chi-squared tests indicate that sophistication variables are not independent, Cramers degrees of association are quite low (i.e., they are lower than 29.5%). Therefore, our sophistication variables do not overlap.

A comparison of portfolio performance between subsets is then computed. The results (table 1.3) show that sophistication does not help to improve returns. Actually, the difference in performance between investors who hold two types of accounts and their peers is insignificant. Concerning the variable *Foreign assets*, the differences in intercepts (CAPM and Fama-French) are insignificant on average. Yet, in aggregate, investors who trade foreign assets underperform their peers. Nor are the results clear-cut concerning more diversified investors. Indeed, on average, investors sorted in the subset *Diversification=1* outperform their peers sorted in the subset *Diversification=0*. In aggregate, however, the differences in risk-adjusted returns are not significant. Therefore, being more sophisticated is not a guarantee of financial success. Some trading behaviors proper to skilled investors might even penalize their performance.

In short, French investors are no exception to the rule. Their gross and risk-adjusted portfolio returns are negative. This observation also applies to most skilled investors from whom we expect better results. The following section, which is devoted to an analysis of the profitability of investors trades, provides additional evidence regarding this observation.

1.2.2 Trading profitability

To evaluate the cost of trading, we start by adjusting each investor return to a passive benchmark, i.e., the monthly returns that investors could have earned if they had kept their portfolio as it was at the beginning of the year.[7] These returns represent the performance that investors could have earned with passive portfolio management (i.e., no transactions) starting with the first day of the considered year. If investors had kept their portfolio as it was at the start of the year, on average, they could have obtained a monthly return of 0.92% (t=1.13). Passive monthly returns are deducted from actual returns to compute the adjusted returns to passive benchmark. Two 96-month time-series of adjusted returns are then computed. As conducted previously, the averages constituting the time-series are equally weighted in one case and value-weighted in the second case:

$$Adjusted\,Average\,Monthly\,Return = \frac{1}{N}\sum_{i=1}^{N}(Monthly\,Return_{i,t}) - (Passive\,Monthly\,Return_{i,t}) \quad (1.5)$$

[7]Results are similar if we use the portfolio as it was at the start of July.

$$Adjusted\,Aggregate\,Monthly\,Return = \frac{1}{\sum PV_{i,t}} \sum_{i=1}^{N} [(Monthly\,Return_{i,t}) - (Passive\,Monthly\,Return_{i,t})] * PV_{i,t} \quad (1.6)$$

The mean of the adjusted returns time-series is equal to -0.21% (t=-2.2) for the average investor and -0.13% (t=-1.2) in aggregate. Although both returns are negative, only the average investor result is significantly different from zero at a 5% confidence level. Hence, because investors hurt their performance by trading, they would be better off applying a *buy and hold* strategy.[8] This conclusion is widely documented, and proponents of behavioral finance suggest that one possible explanation for the tendency to (over)trade is overconfidence (Odean, 1999; Barber and Odean, 2001, 2002; Glaser and Weber, 2007; Gervais and Odean, 2001; Statman, Thorley, and Vorkink, 2006).[9] Glaser and Weber (2007) show, for example, that individual investors who think they are above average in terms of investment skill or past performance trade more than other investors. Odean (1999) demonstrates that overconfidence results in poor decision making.

Following Odean (1999) we test whether ex-post returns of the stocks bought by investors are higher than ex-post returns of the stocks sold by investors, ignoring transaction costs. Ex-post returns are computed over T (T=three-month, six-month and one-year) trading periods subsequent to the trades. If the same stock is purchased

[8]In this work, we show that no trading is better than the actual trading performed by investors; however, some trading might be needed, for example, for liquidity purposes or to rebalance portfolios.

[9]Overconfidence is a psychological concept that can manifest itself in the following forms: miscalibration of probabilities (Lichtenstein and Fischoff, 1981), better than average effect (Cooper, Woo, and Dunkelberg, 1988), illusion of control (Langer and Roth, 1975), and unrealistic optimism (Weinstein, 1980).

(sold) by different investors on the same day, each trade is counted as a distinct observation to account for the intraday volatility. The average return on horizon T for the securities bought is

$$Average\,return\,on\,stocks\,bought_T = \frac{1}{N}\sum_{i=1}^{N} R_{(j,i,i+T)} \tag{1.7}$$

where $R_{(j,i,i+T)}$ is the return of stock j between day i and $i+T$. The average return on stocks sold is computed similarly.

Note that the statistical significance of these results is tested based on a non-parametric test. To compare the average returns on stocks bought and sold, we cannot employ a classical statistical test of means that requires independence in the observation. Indeed, a security can be traded by different investors on more than one date. Because ex-post returns are estimated on three-month, six-month and one-year horizons, the returns of the stock traded in these three cases are not independent. A security may also be traded by the same investor on the same day. In short, as returns are averaged during the trading histories of investors and across investors, returns are likely to overlap. We estimate statistical significance conducting a Wilcoxon test of differences. The average ex-post return on stocks purchased (resp. sold) is determined separately for each investor during three chosen horizons of T (T=three-month, six-month and one-year). The distribution of all individual average returns is then constructed for stocks purchased and sold. A comparison between these distributions is realized by the Wilcoxon test. More formally, we test whether the samples of returns of stocks purchased and sold come from populations with the same medians and the same continuous distributions.

Ex-post returns related to purchases and sales are presented in table 1.4. Panel A reports the results for the entire period. For the three-month (six-month, one-year) horizon, the securities sold significantly outperform the securities bought by 0.71% (1.13%, 1.79%, respectively). We exploit the feature of the dataset period to evaluate whether the differences between ex-post returns on buys and sales are constant in bullish and bearish markets. Consistent with section 1, we choose the Eurofidai value-weighted market index to study the market evolution during our dataset period. Between 1999 and 2006, three sub-periods stand out (see Figure 1.1): first, the dotcom bubble from 1999 to September 2000; second, the post-dotcom bubble, which bottomed out in March 2003; and third, an increase from 2003, which continues even after 2006. Therefore, the sample is split into three sub-periods. The results are presented in Panels B, C and D. Concerning the first and the second sub-periods, the results are quite similar to those obtained for the whole period. Indeed, on each horizon, the stocks purchased significantly underperform the stocks sold. For instance, the difference between the ex-post return on stocks purchased and sold on a three-month horizon is -0.29 for 1999 to 2000 and -1.67% for 2000 to 2003. The results for the 2003 to 2006 sub-period depict a different story because the securities bought outperform the securities sold on the three-month and the six-month horizon. Although the differences are statistically significant, they do not exceed 0.06% on the three-month horizon and 0.02% on the six-month horizon. The reverse pattern is observed for the one-year horizon. Yet the difference between the buys and sales ex-post return is far lower (-0.08) than that computed for the other sub-periods (-1.18% for 1999 to 2000 and -2.34% for 2000 to 2003). Therefore, these values are not economically significant. For comparison, between 1991 and 1996, the stocks bought by U.S. investors underperformed the stocks that they sold by 1.36% on an 84-day horizon, 3.31% on a 252-day horizon and 3.32% on a 2-year horizon (Odean, 1999).

To summarize, for the whole dataset period, the stocks purchased exhibit lower returns than the stocks sold. This observation indicates that investors do not make profitable trades and should therefore trade less. This result is confirmed by the analysis of the two sub-periods, 1999 to 2000 and 2000 to 2003. During the sub-period from 2003 to 2006, the profitability of buy trades is close to the profitability of sell trades. Yet, those results are computed before taking into consideration the transaction costs of buying and selling stocks. In other words, the actual profitability of these trades is even worse than the numbers above indicated.

The robustness of this result (i.e., ex-post return on buys is lower than ex-post return on sales) is tested by adopting a calendar portfolio approach, illustrated in Figure 1.2. Each month t, we build a Buy portfolio of all securities bought and a Sale portfolio of all securities sold by investors during a portfolio formation period. No matter the quantity traded by investors, for each occurrence of a purchase, one unit of the security bought is added to the Buy Portfolio. Similarly, for each occurrence of a sale, one unit of the security sold is added to the Sale Portfolio. This test is computed with a three month-, six month- and one year- formation period. The average monthly return of the Buy portfolio and the Sale portfolio is then evaluated on month $t+1$. This procedure is realized for 84 (90 and 93) months t, corresponding to the formation period equal to one year (six months and three months, respectively). Thus, we obtain 84-, 90- and 93-month time-series of calendar portfolio returns. Three measures of performance are then estimated. The first one is simply the difference of the average monthly return between the Buy portfolio and the Sale portfolio. Second, we regress the time-series of the Buy portfolio minus the time-series of the Sale portfolio monthly calendar returns on the market index. Third, we employ the three-factor model developed by Fama and French (1993). In both last cases, we compute alphas and factors based on an ordinary least squares (OLS) estimation.

$$Rp_{B,t} - Rp_{S,t} = \alpha_p + \beta_p(Rm_t - rf_t) + \epsilon_t \tag{1.8}$$

$$Rp_{B,t} - Rp_{S,t} = \alpha_p + \beta_p(Rm_t - rf_t) + z_p SMB_t + h_p HML_t + \epsilon_t \tag{1.9}$$

where $Rp_{B,t}$ is the return of the Buy portfolio for the month t, $Rp_{S,t}$ is the return of the Sell portfolio for the month t, Rm_t is the monthly return on a value-weighted market index, β_p is the market beta, rf_t is the monthly risk-free rate and ϵ_t is the error term. In the 3-factor model, SMB_t is the monthly return on a value-weighted portfolio of small stocks minus the monthly return on a value-weighted portfolio of large stocks and HML_t is the monthly return on a value-weighted portfolio of high book-to-market stocks minus the monthly return on a value-weighted portfolio of low book-to-market stocks. Variables z_p and h_p are coefficients on factors size and book-to-market.

Note that the Breusch-Pagan test and White's general test do not detect heteroskedasticity. Table 1.5 reports the results. Panel A presents the average monthly calendar returns for the Buy portfolio and the Sale portfolio as well as the difference between the returns. Panel B gives the alpha estimates. For the three-month and the six-month portfolio formation period, the difference between the average return of the Buy portfolio and the Sale portfolio is significantly negative, as are the CAPM and the Fama-French intercepts. For the one-year portfolio formation period, the results are negative but insignificant in the risk-adjusted return cases.

This test confirms that French investors are making poor portfolio choices and that they would be better off applying a passive strategy instead of self-managing their portfolios.

1.3 Conclusion

The present study provides additional evidence with respect to the poor trading abilities of individual investors. We analyze the portfolio performance of 56,723 French retail investors for the 8 years ending in December 2006. French investors exhibit negative risk-adjusted returns on their portfolio and buy stocks with weak future performance. These patterns are robust to various market trends and are also observed for most sophisticated investors. Our main point is that, similarly to their American, Finnish and Taiwanese peers, French retail investors trade to their detriment. This main result leads researchers to conclude that individual investors should at a minimum follow a passive strategy, or even better, rely on professional investors to manage their wealth. Several solutions explain that investors might ignore this common advice. First, we mentioned that investors are prone to overconfidence and may believe that they are all above average; in other words, they may think that they have superior skills and information. Second, many of them consider trading as an entertainment. Lastly, some people who aspire to be millionaires expect to reach their aspirations through stock trading.

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Figure 1.1
Value-weighted index between 1999-2006

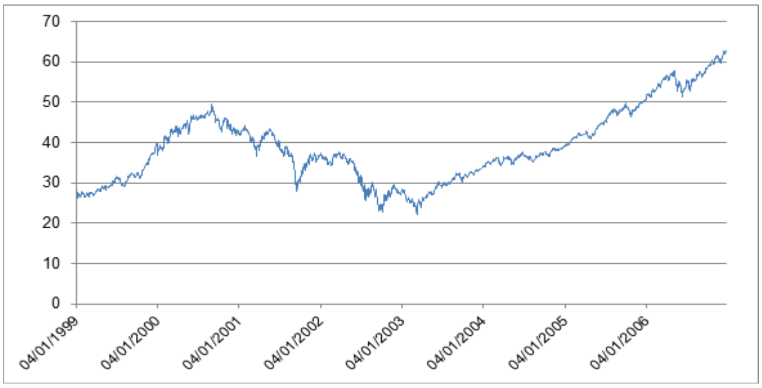

Figure 1.2
Calendar portfolio methodology

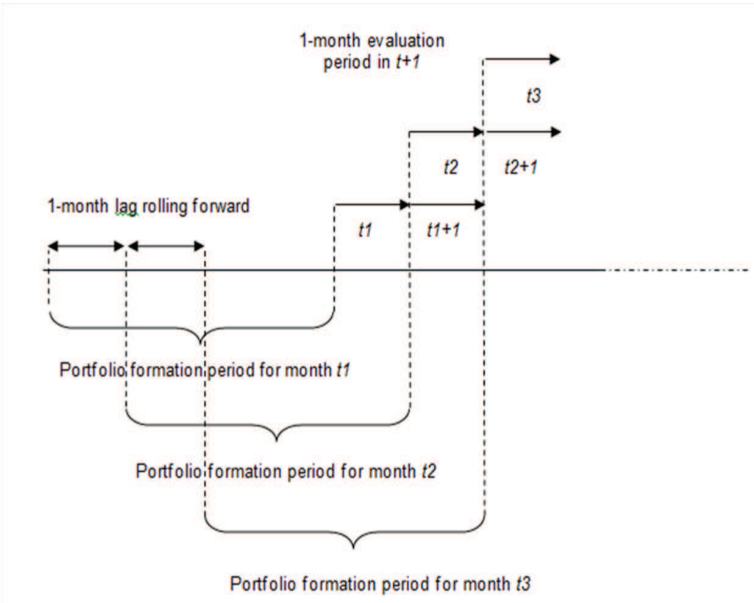

Table 1.1
Descriptive statistics

	Mean	St. deviation	Median	20%	40%	60%	80%
	Panel A: Purchases						
Average turnover (%)	19.77	53.98	8	3.16	5.98	11.05	24.52
Average trade size (Euros)	2,498	12,703	394	41	233	565	2,050
Average quantities	136	1,030	11	1	6	19	74
	Panel B: Sales						
Average turnover (%)	19.19	33.08	7.55	2.86	5.57	10.46	23.41
Average trade size (Euros)	2,488	12,8	381	46	224	636	2,000
Average quantities	130	1,022	10	1	6	18	57
	Panel C: Portfolios						
Average diversification	6.2	6.3	4.3	2	3.4	5.4	9
Average portfolio value (Euros)	26,256	109,550	8,852	2,593	6,161	12,729	29,371
Average return (%)	-0.24	3.07	0.09	-1.32	-0.26	0.38	1.09

This table reports descriptive statistics for 56,723 French investors over the period from 1999 to 2006. Panel A and B are dedicated to monthly trading activity. Panel A reports the statistics relative to buy trades and Panel B reports the statistics relative to sell trades. Averages are computed across 96 months. The individual monthly turnover is the monthly market value of shares purchased in month t, or sold in month t by the investor, divided by the average market value of portfolio during month t. The individual monthly trade size is the amount traded by the investor during month t. The monthly quantity traded corresponds to the number of stocks traded by the investor during the month t. Panel C reports portfolios monthly average characteristics. Diversification is computed as the number of stocks in portfolio at the start of each month. The portfolio value is evaluated each start of month.

Table 1.2
Portfolio performance - Full sample

	Coefficient Estimates on:				
	$Rp_t - r_{f_t}$ (%)	$R_m - r_{f_t}$ (%)	HML	SMB	R^2
		PANEL A: Average results			
CAPM	-0.6**	1.33***			86.57
	(-2.1)	(27.4)			
Fama-French	-0.87***	1.44***	-0.06	0.31***	88.22
	(-2.8)	(-24)	(-0.8)	(3.5)	
		PANEL B: Aggregate results			
CAPM	-0.52*	1.3***			85.26
	(-1.7)	(23.3)			
Fama-French	-0.86***	1.41***	-0.03	0.33***	87.31
	(-2.7)	(23.6)	(-0.5)	(3.7)	

Percentage monthly returns over the period from 1999 to 2006 are computed for 56,723 investors from a French brokerage house. Panel A presents results for the return on a portfolio that mimics the investment of the average household. Panel B presents results for the return on a portfolio that mimics the aggregate investment of all investors. Own-benchmark excess return is the return on the investor portfolio minus the return on the portfolio she held at the beginning of the year. The excess return on the market index is computed with a value-weighted and an equally-weighted index. The CAPM intercepts and coefficient estimates result from a time-series regression of the household excess return on the market excess return. The Fama-French intercepts and coefficient estimates result from a time-series regression of investor excess return on the market excess return, a zero-investment book-to-market portfolio and a zero-investment size portfolio. T-stats are presented in parentheses. ***, **, * indicate that results are significant at the 1%, 5% and 10% levels.

Table 1.3
Portfolio performance - Segmentation based on sophistication

	CAPM intercept (%)	**Three-factor intercept (%)**
	Panel A: Average results	
Two accounts=1	-0.55** (-2)	-0.81*** (-2.8)
Two accounts=0	-0.67** (-2.1)	-0.96*** (-2.9)
Two accounts=1 - Two accounts=0	0.13 (1.3)	0.15 (1.5)
Foreign assets=1	-0.60** (-2)	-0.88*** (-2.8)
Foreign assets=0	-0.60** (-2.1)	-0.87*** (-3)
Foreign assets=1 - Foreign assets=0	-0.005 (-0.06)	-0.02 (-0.2)
Diversification =1	-0.50** (-2)	-0.75*** (-2.8)
Diversification=0	-0.74** (-2.1)	-1.04*** (-2.7)
Diversification=1 - Diversification=0	0.24** (2.5)	0.28*** (2.7)
	Panel B: Aggregate results	
Two accounts=1	-0.48* (-1.7)	-0.82*** (-2.7)
Two accounts=0	-0.58* (-1.8)	-0.93*** (-2.8)
Two accounts=1 - Two accounts=0	0.1 (1)	0.1 (1)
Foreign assets=1	-0.56* (-1.8)	-0.89*** (-2.8)
Foreign assets=0	-0.27 (-1)	-0.66*** (-2.4)
Foreign assets=1 - Foreign assets=0	-0.29*** (-3.2)	-0.24** (-2.5)
Diversification =1	-0.51* (-1.8)	-0.85*** (-2.8)
Diversification=0	-0.49 (-1.4)	-0.88*** (-2.3)
Diversification=1 - Diversification=0	-0.02 (-0.21)	0.03 (0.3)

Percentage monthly returns over the period from 1999 to 2006 are computed for 56,723 investors from a French brokerage house. Performances are compared between sophisticated and non-sophisticated investors. Investors who trade foreign assets and who hold two types of accounts are considered to be sophisticated. In addition, we consider that investors whose level of diversification is above the median level computed on all investors are sophisticated. Panel A presents results for the return on a portfolio that mimics the investment of the average household. Panel B presents results for the return on a portfolio that mimics the aggregate investment of all investors. Own-benchmark excess return is the return on the investor portfolio minus the return on the portfolio she held at the beginning of the year. The excess return on the market index is computed with a value-weighted and an equally-weighted index. The CAPM intercepts and coefficient estimates result from a time-series regression of the household excess return on the market excess return. The Fama-French intercepts and coefficient estimates result from a time-series regression of investor excess return on the market excess return, a zero-investment book-to-market portfolio and a zero-investment size portfolio. T-stats are presented in parentheses. ***, **, * indicate that results are significant at the 1%, 5% and 10% level.

Table 1.4
Profitability of buys and sales

	3 months	**6 months**	**1 year**
	Panel A: 1999-2006		
Number of purchases	4,148,143	4,148,143	4,148,143
Number of sales	3,752,934	3,752,934	3,752,934
Purchases Returns	1.21%	1.74%	2.22%
Sales Returns	1.92%	2.86%	4.01%
Difference	-0.71%***	-1.13%***	-1.79%***
	(47.1)	(53.8)	(66.4)
	Panel B: 1999-2000		
Number of purchases	1,280,703	1,280,703	1,280,703
Number of sales	1,109,516	1,109,516	1,109,516
Purchases Returns	5.80%	6.61%	2.12%
Sales Returns	6.09%	7.11%	3.30%
Difference	-0.29%***	-0.50%***	-1.18%***
	(7.8)	(3.1)	(7.6)
	Panel C: 2000-2003		
Number of purchases	1,167,879	1,167,879	1,167,879
Number of sales	996,961	996,961	996,961
Purchases Returns	-10.03%	-15.75%	-20.81%
Sales Returns	-8.36%	-13.60%	-18.47%
Difference	-1.67%***	-2.15%***	-2.34%***
	(50.5)	(54.1)	(63.2)
	Panel D: 2003-2006		
Number of purchases	1,694,207	1,694,207	1,694,207
Number of sales	1,641,951	1,641,951	1,641,951
Purchases Returns	5.46%	10.10%	18.20%
Sales Returns	5.40%	10.08%	18.28%
Diffrence	0.06%***	0.02%***	-0.08%***
	(2.5)	(3.4)	(3.1)

Average returns are calculated for the 3-month, 6-month and 1-year horizons following purchases and following sales of 56,723 investors from a French brokerage house. Median are presented in parentheses. Panel A reports results for the whole period. Panel B, C and D present results for the 1999-2000, 2000-2003 and 2003-2006 sub-periods. Significance testing is performed with a non-parametric Wilcoxon rank sum test. Z-values are presented in parenthesis, and ***, **, * indicate that results are significant at the 1%, 5% and 10% level.

Table 1.5
Calendar time portfolio

Formation Period	3 months	6 months	1 year
Panel A: Buy and Sale portfolio returns			
# transactions	10,830,001	21,024,474	40,182,989
"Buy portfolio" returns (%)	0.84	0.69	0.43
"Sale portfolio" returns (%)	1.02	0.87	0.55
Difference (%)	-0.17**	-0.18**	-0.12
	(-2.1)	(-2.5)	(-1.6)
Panel B: CAPM			
Alpha (%)	-0.19**	-0.19***	-0.107
	(-2.4)	(-2.6)	(-1.5)
Beta	0.03*	0.02	-0.018
	(1.9)	(1.5)	(-1.4)
Panel C: Fama-French three factors			
Alpha (%)	-0.18**	-0.19**	-0.02
	(-2)	(-2.2)	(-0.3)
Beta	0.023	0.019	-0.02
	(1.3)	(1.2)	(-1.4)
HML	0.009	0.0002	-0.05***
	(0.4)	(0.011)	(-3)
SMB	-0.02	-0.05	0.012
	(-0.8)	(-0.2)	(0.6)

We construct calendar-time portfolios consisting of all purchase (sale) events during a portfolio formation period (3 months, 6 months and 1 year). Panel A reports the average calendar time return on the Buy and Sell portfolio. Difference is the difference between the average returns on the two portfolios. Panel B gives the CAPM intercepts and coefficient estimates from a time-series regression of the household excess return on the market excess return. Panel C gives the Fama-French intercepts and coefficient estimates from a time-series regression of household excess return on the market excess return, a zero-investment book-to-market portfolio and a zero-investment size portfolio. t-stats are presented in parentheses. ***, **, * indicate that results are significant at the 1%, 5% and 10% level.

Chapter 2

Investors' aspirations and portfolio performance

Forthcoming in *Finance Research Letters*

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Abstract

Based on a large database of individual investors, I analyze the impact of personal financial goals on portfolio performance. I stress the role played by latent investor aspirations as defined in the Behavioral Portfolio Theory framework. I identify two opposite profiles of investors. High-aspirations investors trade more and hold riskier portfolios than the average investor. By contrast, low-aspirations investors are more diversified than the average investor. I find that when controlling for diversification, turnover and usual risk factors, high-aspiration investors underperform their peers, whereas low-aspirations investors outperform them.

2.1 Introduction

It is widely documented that individual investors make detrimental choices in their transactions, such as buying stocks with weak future performance (Odean, 1999; Barber and Odean, 2000; Hvidkjaer, 2008). The global evidence that individuals lose money on their trades obscures a considerable heterogeneity in investor profiles. Research shows that the cross-sectional variation in performance can be traced to observable characteristics of investors such as socio-demographic variables (Barber and Odean, 2000, 2001; Korniotis and Kumar, 2009a) or cognitive capacities (Seru, Shumway, and Stoffman, 2010; Grinblatt, Keloharju, and Linnainmaa, 2011). Usually, the authors make the implicit assumption that investors who share the same observable features have homogenous preferences. It follows that these preferences lead to similar trading behaviors. However, it could be that investors in the same socio-demographic group differ in their goals, resulting in different trading choices. In this work, I offer an original comparison of the performance of individual investors who differ by their latent aspirations.

Aspiration is a concept borrowed from psychology. According to Siegel (1957), level of aspiration refers to the particular achievement goal for which the person strives. In the context of risky choices, aspirations are defined as pre-determined benchmark return used by a decision maker to translate monetary outcomes into gains and losses (Payne, Laughhunn, and Crum, 1980). Aspiration levels are determined by two main processes. On the one hand, people get used to repeated stimuli, which are provided by their consumption habits. In fact, people tend to adapt quickly to higher income and consumption levels. As a consequence, additional material goods provide extra pleasure which wears off over time. On the other hand, people compare their social situation with others. It is not the absolute level of income that matters most, but rather ones position relative to other individuals (Stutzer, 2004).

Previous research suggests that aspiration levels play a key role in decision-making.[1] Concerning portfolio choices, Hoffmann, Shefrin, and Pennings (2010) use a combination of survey data and trading records of 5,500 investors to analyze how aspirations impact the portfolios they select and the return they earn. Based on a large European database containing more than 4 million trades, I explore more deeply the link between aspirations and performance.

I evaluate investor aspirations according to the Behavioral Portfolio Theory (BPT) framework developed by Shefrin and Statman (2000). In this approach, investors choose their portfolio to match their aspiration levels. The composition of the BPT optimal portfolio is different from the Capital Asset Pricing Model (CAPM) optimal portfolio. BPT investors consider their portfolios as pyramids of assets. The riskless instruments are at the bottom, and the riskier instruments are at the top.[2] The layers of assets are associated with aspirations. The bottom layer addresses the desire for security and is intended by the investor to avoid poverty. The top layer includes the riskiest assets that have the potential for larger returns. According to Shefrin (2005),

[1] See for example March and Shapira (1987); Payne, Laughhunn, and Crum (1980); Brown, De Giorgi, and Sim (2012).

[2] I refer to the multiple mental accounts version of BPT.

Treasury bills are for investors with very low aspiration levels, whereas investors with higher aspiration levels choose stocks. Investors with even higher aspiration levels choose out of the money call options and lottery tickets. Along the same lines, Statman (2002) (p.18) argues that "*Lottery tickets are best for upside potential doers with high aspirations and little money* [...] *Upside potential doers with more money and lower aspirations can meet their needs through call options, however, and those with even lower aspirations can buy stocks.*" To understand how aspirations drive the choice of particular securities, a simple version of the BPT model can be found in the appendix (2.3).

In this paper, I compare the portfolio performance of investors who have low and high aspiration levels. Following Shefrin (2005) and Statman (2002), I identify two profiles of investors based on the securities they trade. More precisely, I consider that investors who trade derivatives have high aspiration levels, whereas investors who trade bonds have low aspirations. The labels High aspirations investors and Low aspirations investors hide different preferences and behaviors. First, aside aspiration levels, the choice of derivative assets could suggest that the investor is risk tolerant. However, a risk seeking behavior does not necessarily indicate a risk-lover investor. It might be that high aspiration individuals do not like risk by itself, but accept gambles because they want to improve their standard of living.

Second, the trading of derivatives could reveal an overconfident investor. Indeed, Nosic, Weber, and Glaser (2013) demonstrate that subjects exhibiting a higher degree of overconfidence are likely to invest into riskier portfolios.

Consistently with these assumptions, high-aspirations investors prove to be overconfident. They trade excessively (which is the most common manifestation of overconfidence in finance[3]) and they hold riskier portfolios. By contrast low-aspirations investors are more diversified than the average investor and build less risky portfolios. I provide evidence that investors with low aspirations exhibit higher portfolio returns and that those with higher aspirations receive lower returns compared with their peers. My main contribution is that overconfidence and risk preferences do not yield my results. In fact, I show that when controlling for the usual investment risk factors, turnover and diversification, the differences in performance persists. Therefore, unlike Hoffmann, Shefrin, and Pennings (2010) conclusion, I find that the underperformance of high aspiration investors is not linked only to their trading activity.

This paper is organized as follows: section 2 is devoted to the empirical analysis, and section 3 contains the conclusions of my research.

2.2 Empirical study

2.2.1 Data and subsets of investors

The primary data set is provided by a large European brokerage house. I obtained the daily transactions records of 26,166 retail investors who conducted 4,481,493 transactions between 1999 and 2006. Table 2.1 presents descriptive statistics for

[3]See Odean (1999); Barber and Odean (2000); Glaser and Weber (2007).

the monthly trading activity of investors and their portfolios.

I proxy aspiration levels based on direct indicators. To accomplish this, I segment investors based on the securities they trade. I follow Shefrin (2005) and Statman (2002) and define investors who trade bonds (in addition to stocks) but do not trade derivative assets as having low aspiration levels. Second, investors who trade derivative assets (in addition to stocks) but do not trade bonds are assumed to have high aspiration levels. Therefore, the following subsamples are created: High-aspirations investors, Low-aspirations investors and Other investors. A total of 16.01% of investors trade warrants but not bonds, 6.77% trade bonds but not warrants, 3.5% trade both, and most investors do not trade any of those products. In total, 77% of the population is sorted into the subset Other investors, which constitutes the benchmark group, and is considered to have average aspiration levels.

Hoffmann, Shefrin, and Pennings (2010) demonstrate that investors who trade to speculate have high aspiration levels. They take more risks and are more prone to overtrading than investors with lower aspirations. In addition, male investors are especially well represented in this segment. By contrast, they find that investors whose primary objective is to build a financial buffer or save for retirement have lower aspirations, take less risks and are more diversified. Consistent with these earlier conclusions, I find that the investors I assume to have high aspirations trade much more frequently than their peers. The average turnover (21.7%) for this subset is three times the average turnover for low-aspirations investors and twice the average turnover computed for the Other investors subset. The high-aspiration subset is 89.7% male, while the low-aspiration group is 82.5% male. The latter hold the most diversified portfolios; the average number of stocks in their portfolio is 12 and the median is 9 assets. Among the high-aspiration investors and the Other investors subset, the average is 8, and the median is 6 assets. Therefore, the soundness of my variables used to proxy aspirations is confirmed.

2.2.2 Aspiration and portfolio performance

For the purpose of this analysis, I calculate portfolio monthly returns of investors based on daily returns. I then create two 96-month time-series of returns. In the first case, the averages constituting a time-series are computed using an equal weight for each individual investor. In the second case, I weight each investor using the investors monthly portfolio value (based on portfolio values at the start of each month). Value-weighted averages enable the analysis to be run at an aggregate level. I start with an estimation of the $CAPM - \alpha$ by regressing the monthly excess return earned by individual investors (on average and in aggregate) on the market excess return. Then, I employ the three-factor model developed by Fama and French (1993). I thus estimate the following 96-month time-series regressions

$$Rp_t - rf_t = \alpha_p + \beta_p(Rm_t - rf_t) + \epsilon_t \tag{2.1}$$

$$Rp_t - rf_t = \alpha_p + \beta_p(Rm_t - rf_t) + z_pSMB_t + h_pHML_t + \epsilon_t \tag{2.2}$$

where Rp_t is the average (aggregate) monthly return of investors, Rm_t is the monthly return on a market index, β_p is the market beta, rf_t is the monthly risk free rate (1-month Euribor), and ϵ_t is the regression error term. In equation 2.2, SMB_t is the monthly return on a value-weighted portfolio of small stocks minus the monthly return on a value-weighted portfolio of large stocks, and HML_t is the monthly return on a value-weighted portfolio of high book-to-market stocks minus the monthly return on a value-weighted portfolio of low book-to-market stocks. Coefficients z_p and h_p are related to the factors size and book-to-market.[4]

The results presented in table 2.2 show that high-aspiration investors significantly underperform their peers in the Other investors subsample, whereas low-aspirations investors outperform their peers. As trading preferences are a concrete reflection of investors aspiration, I focus on the risk coefficients related to beta and the size factor (SMB). High-aspirations investors hold portfolios with greater betas and have a stronger preference for small stocks than their peers. Conversely, low-aspirations investors hold lower market risk portfolios and tilt toward small stocks less than average investors do.[5] However, risk-adjusted returns indicate that, taking into consideration investment style differences, the main observation that high-aspiration investors underperform their peers persists.

[4] SMB_t and HML_t factors are provided by Eurofidai and calculated according to the Fama and French (1993) methodology.

[5] Note that the portfolios of high aspiration investors exhibit a significantly greater skewness (0.1007) than the portfolios of low aspiration investors (0.0739). For a detailed analysis on skewness and performance, see Kumar (2009).

I test the robustness of my main finding by running the following linear regression model on the whole sample:

$$\begin{aligned} Perf_i = a + b_1(High\,aspirations\,investors_i) + \\ b_2(Low\,aspirations\,investors_i) + b_3 ln(Diversification_i) + \\ b_4 ln(Turnover_i) + b_5(Gender_i) + b_6 ln(Portfolio\,Value_i) + e_i \end{aligned} \quad (2.3)$$

where $Perf_i$ is the performance of the investor i, evaluated by the average gross geometric return in a first case, by the individual CAPM-α in a second case, and by the individual Fama-French intercept in a third case. The regression coefficients for the explanatory variables are b_1 and b_2; b_3, b_4, b_5 and b_6 are the coefficients for the control variables; and e_i is the residual.

The variables *High-aspirations investors* and *Low-aspiration investors* are dummy variables. First, it is apparent from the results in table 2.3 that high-aspiration investors underperform their peers and that low-aspiration investors outperform their peers. The coefficient for Diversification is positive with the dependent variables being the geometric average and the $CAPM - \alpha$, whereas it is negative with the Fama-French intercept. Therefore, the role of Diversification is not clear cut. The results for the *Turnover* control variable are consistent with the well-known result that excessive trading hurts the performance of individual traders (Barber and Odean, 2000). Indeed, the coefficient is negative in each model. Similarly, females perform better than males. Finally, the results indicate that investor wealth positively affects portfolio performance. Note that the *Portfolio Value* and *Diversification* variables are highly correlated (73%). Though the control variables have an influence on performance, their effects do not seem to override the role of aspiration levels. In the following test, I re-compare portfolio performance between subsets. Results control for trading activity and diversification level.

I sort investors based on their diversification and turnover levels. First, Low/High turnover investors and Low/High diversification investors are identified with Low and High referring to the value of the investors turnover (diversification), which is below or above the median turnover (diversification) computed across all investors. Second, among Low/High turnover investors and Low/High diversification investors, high-aspiration investors and low-aspiration investors are identified.

The turnover-controlled differences indicate that the underperformance of high-aspirations investors is not challenged by most active investors (table 2.4). Though the differences in risk-adjusted returns between high-aspiration investors and other investors are lower than the ones computed for the low-turnover subsets, they are still negative. Similarly, the better performance of low-aspirations investors persists with the turnover controls, and differences are positive and significant in all cases (except in aggregate for high frequency traders with the CAPM regression). Controlling for portfolio diversification (table 2.5), high-aspirations investors underperform other investors in low- and high- diversification groups. However, the result relating to low-aspirations investors is not clear-cut. Indeed, in aggregate for low-diversified investors, better performance is not observed. Therefore, diversification may be part of the explanation for the higher returns achieved by low-aspirations investors. In all other cases, low-aspirations investors outperform others including the least and most diversified investors.

In conclusion, high turnover negatively affects performance but it does not fully explain why high-aspirations investors (who trade more than the average) exhibit weaker returns than their peers. Along the same lines, the diversification level of investor portfolio does not fully explain why low-aspirations investors outperform.

2.3 Conclusion

In this work, I evaluate how aspirations influence the portfolio performance of individual investors. Focusing on latent characteristics, I present an original contribution to the literature on portfolio performance. Previous research has focused on how socio-demographic features or cognitive capacities explain the existing heterogeneity in performance. I adopt a new perspective and analyze the role of individual investing goal. I define aspirations according to the Behavioral Portfolio Theory framework. Relying on direct measures, two profiles of investors are identified. Investors who have high aspirations trade more and hold riskier portfolios than the average. By contrast, low-aspirations investors are more diversified. The most significant findings to emerge from this study are that, controlling for turnover, diversification and risk factors, high-aspirations investors underperform their peers, whereas low-aspiration investors outperform their peers. Hence, individual aspiration is a key variable in explaining the highlighted cross-sections in the portfolio performance of investors.

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Appendix

In Behavioral Portfolio Theory, investors aim at maximizing their expected wealth while securing a minimal target value. More precisely, they set an acceptable probability for their wealth to reach this target value, which corresponds to their aspiration level

$$P(\tilde{W} < s) \leq \alpha \tag{2.4}$$

where $\tilde{W}$ is the future wealth distribution, A is the aspiration level, α is the maximum acceptable probability of not reaching A. This aspiration level is not unique. Investors divide their overall portfolios into mental account sub-portfolios, with each mental account devoted to a goal (retirement income, education expenses, bequests, etc.) and characterized by an aspiration level.

At the same time, investors are driven by fear and hope. On the one hand, they wish to secure their wealth, and on the other hand they want to reach a high level of wealth. These two emotions operate on the willingness to take risk by altering the probabilities of returns distribution. Fear (respectively hope) operates through an overweighting of probabilities attached to the worst (respectively best) outcomes relatively to the others. Hence, fear leads individual to compute $E(W)$ with subjective pessimistic probabilities. Along the same lines, hope leads individual to compute $E(W)$ with subjective optimistic probabilities. Therefore investors substitute $E_\pi(W)$ to $E(W)$. Note that overconfidence could be related to BPT through an optimistic view regarding the occurrence of the best outcomes. As a result, the optimization program of the BPT investor can be defined as

$$Max\, E_{\pi}(\tilde{W})\, t.q.\, P(\tilde{W} < A) \leq \alpha \tag{2.5}$$

BPT investors consider their portfolios as pyramids of assets. The riskless instruments are at the bottom, and the riskier instruments are at the top. The layers of assets are associated with aspirations. BPT investors proceed in two steps to set their portfolio. First, they satisfy the security criteria. Therefore they allocate their wealth in such a way that they ensure to obtain their aspiration level. Second, they invest the remaining wealth in securities characterized by a high potential payoff.

According to Shefrin (2005), Treasury bills are for investors with very low aspiration levels, while stocks are appropriate for investors with higher aspiration level. Investors with even higher aspiration levels choose out of the money call options and/or lottery tickets. Investors with low aspiration levels secure their minimal target wealth with riskless assets (bonds). The next layer is composed of stocks. Therefore, they allocate all their wealth in the bottom layers of the pyramid of assets to reach their moderate goals. By contrast, investors with high aspiration levels cannot reach their goals other than through stocks and lottery-like payoff assets. They secure their minimal target wealth by allocating one part of their money in the stock layer. The remaining wealth is invested in derivative assets, to satisfy their highest aspiration levels. Hence, they are located on the top part of the pyramid of assets

Table 2.1
Descriptive statistics

	Mean	St. dev.	Median
Panel A: Purchases			
Average Turnover (%)	14.32	63.88	6.32
Average trade size (Euros)	2,725	12,711	588
Average quantities	142	861	16
Panel B: Sales			
Average Turnover (%)	13.37	23.67	6.17
Average trade size (Euros)	2,73	12,856	569
Average quantities	134	845	15
Panel C: Portfolios			
Average diversification	8	7.3	6.1
Average portfolio value	27,447	119,070	10,531
Average return (%)	0.01	2	0.19

This table reports descriptive statistics over the period 1999 to 2006 for 26,166 French investors. Panel A and B are dedicated to monthly trading activity. Panel A reports the statistics relative to buy trades and Panel B reports the statistics relative to sell trades. Averages are computed across 96 months. The turnover is the monthly market value of shares purchased in month t, or sold in month t by the investor, divided by the average market value of her portfolio during month t. The trade size is the amount traded by the investor during month t. The quantity traded corresponds to the number of stocks traded by the investor during the month t. Panel C presents portfolios monthly average characteristics. Diversification is computed as the number of stocks in portfolio at the start of each month. The portfolio value is evaluated each start of month. The portfolio monthly return is computed based on daily return.

Table 2.2

Regression coefficient estimates for the subsets based on investors' profile

	CAPM		**Three-factor**			
	Intercept	$R_m - r_f$	Intercept	$R_m - r_f$	HML	SMB
Panel A: Average results						
High aspirations investors	-0.7293**	1.4304***	-1.1449***	1.5674***	-0.0554	0.4100***
	(-2.2)	(22.5)	(-3.3)	(23.4)	(-0.6)	(4.1)
Low aspirations investors	-0.3818**	1.1652***	-0.5277***	1.2411***	-0.0892	0.2445***
	(-2.0)	(27.6)	(-2.8)	(27.2)	(-1.5)	(3.6)
Other investors	-0.5337**	1.2853***	-0.7804***	1.3758***	-0.0560	0.2767***
	(-2.0)	(26.0)	(-2.8)	(25.6)	(-0.8)	(3.5)
High aspirations investors - Others	-0.1957***	0.1451***	-0.3645***	0.1916***	0.0006	0.1332***
	(-4.5)	(17.7)	(-8.0)	(21.9)	(0.1)	(10.2)
Low aspirations investors- Others	0.1519***	-0.1201***	0.2527***	-0.1348***	-0.0332***	-0.0322***
	(4.3)	(-18.1)	(6.7)	(-18.8)	(-3.6)	(-3.0)
Panel B: Aggregate results						
High aspirations investors	-0.7074**	1.4379***	-1.1753***	1.5839***	-0.0417	0.4319***
	(-2.0)	(21.4)	(-3.2)	(22.3)	(-0.5)	(4.1)
Low aspirations investors	-0.3652	1.1799***	-0.4561***	1.2749***	-0.1760**	0.3258***
	(-1.6)	(23.0)	(-2.7)	(23.5)	(-2.5)	(4.0)
Other investors	-0.4556	1.2500***	-0.7938***	1.3520***	-0.0212	0.2993***
	(-1.6)	(23.9)	(-2.7)	(24.1)	(-0.3)	(3.6)
High aspirations investors- Others	-0.2518***	0.1879***	-0.3815***	0.2319***	-0.0205*	0.1326***
	(-5.5)	(21.6)	(-7.9)	(25.1)	(-1.7)	(9.7)
Low aspirations investors- Others	0.0904**	-0.0701***	0.3377***	-0.0770***	-0.1547***	0.0265***
	(2.3)	(-9.4)	(8.1)	(-9.7)	(-15.1)	(2.2)

This table reports percentage monthly returns and risk factors coefficients over the period 1999 to 2006. *High aspirations investors* are identified on the basis of derivative asset trading in addition to stocks trading but no bonds trading. *Low aspirations investors* are identified on the basis of bonds trading in addition to stocks trading but no derivative assets trading. The subset *Other investors* contains the rest of the population. Panel A presents results for the gross return on a portfolio that mimics the investment of the average investor. Panel B presents results for the gross return on a portfolio that mimics the aggregate investment of all investors. The CAPM intercept is obtained from a time-series regression of the investor excess return on the market excess return. The three-factor intercept is obtained from a time-series regression of investor excess return on the market excess return, a zero-investment book-to-market portfolio and a zero-investment size portfolio. T-stats are presented in parentheses. ***, **, * indicate that results are significant at the 1%, 5% and 10% level.

Table 2.3
Determinants of the portfolio monthly return

	Geometric Average gross returns	**CAPM intercept**	**Fama-French intercept intercept**
Intercept	-1.5451*** (-16.9)	-0.9774*** (-23.9)	-1.6894*** (-30.6)
High aspirations investors	-0.1944*** (-5.7)	-0.121*** (-7.9)	-0.2473*** (-12)
Low aspirations investors	0.0353 (0.7)	0.0926*** (4.2)	0.1309*** (4.4)
Ln(Diversification)	0.3094*** (13.6)	0.0845*** (8.3)	-0.029** (-2.1)
Ln(Turnover)	-0.0972*** (-8.1)	-0.0397*** (-7.3)	-0.1156*** (-15.9)
Gender	-0.0425 (-1.3)	-0.0466*** (-3.3)	-0.0701*** (-3.7)
Ln(Portfolio Value)	0.0876*** (7.3)	0.0187*** (3.5)	0.0792*** (10.9)
R	4.03	2.09	3.42
Number of observations	26,044	26,06	26,06

This table contains regression coefficients for the linear regression of the individual performance over the period 1999 to 2006. The dependent variable is the Geometric Average gross return in the first column, the CAPM intercept in the second column, and the Fama-French intercept in the third column. The independent variables are the dummies *High aspirations investors* and *Low aspirations investors*. *High aspirations investors* are identified on the basis of derivative asset trading in addition to stocks trading but no bonds trading. *Low aspirations investors* are identified on the basis of bonds trading in addition to stocks trading but no derivative assets trading. *Turnover*, *Diversification*, *Gender* and *Portfolio Value* are control variables. Turnover is computed as an average of monthly turnover, with the monthly turnover equal to the market value of shares purchased in month t, or sold in month t, divided by the average market value of the portfolio during month t. The individual diversification is an average of the number of different stocks in portfolio at the start of each month. The portfolio value is the mean of each start of month portfolio values. Student t appears in parenthesis. ***, **, * indicate that results are significant at the 1%, 5% and 10% level.

Table 2.4

Intercept estimates for the subsets based on investors' profile and turnover

	CAPM intercept (%)				Three-factor intercept (%)			
	PANEL A: Individual results							
Turnover	**Low**		**High**		**Low**		**High**	
High aspirations investors	-0.604**	(-2.2)	-0.820**	(-2.1)	-0.924***	(-3.2)	-1.295***	(-3.2)
Low aspirations investors	-0.341	(-1.6)	-0.489*	(-1.8)	-0.455**	(-2.0)	-0.719***	(-2.9)
Other investors	-0.432*	(-1.9)	-0.738**	(-2.1)	-0.627***	(-2.6)	-1.072***	(-2.9)
High aspirations investors - Others	-0.172***	(-4.7)	-0.082	(-1.5)	-0.297***	(-7.7)	-0.223***	(-4.0)
Low aspirations investors - Others	0.091***	(2.9)	0.248***	(5.5)	0.172***	(5.0)	0.353***	(7.5)
	PANEL B: Aggregate results							
Turnover	**Low**		**High**		**Low**		**High**	
High aspirations investors	-0.642*	(-1.9)	-0.759**	(-2.0)	-1.144***	(-3.3)	-1.192***	(-3.0)
Low aspirations investors	-0.283	(-1.1)	-0.647*	(-1.9)	-0.348	(-1.3)	-0.791***	(-2.7)
Other investors	-0.374	(-1.5)	-0.645*	(-1.8)	-0.669**	(-2.5)	-1.024***	(-2.7)
High aspirations investors - Others	-0.269***	(-6.4)	-0.115**	(-2.1)	-0.474***	(-10.7)	-0.168***	(-3.0)
Low aspirations investors - Others	0.091**	(2.5)	-0.002	(0.0)	0.322***	(8.4)	0.233***	(4.5)

Percentage monthly returns over the period 1999 to 2006 are computed for the subsets *High aspirations investors*, *Low aspirations investors* and *Other investors* for high (above median) and low (below median) turnover levels. *High aspirations investors* are identified on the basis of derivative asset trading in addition to stocks trading but no bonds trading. *Low aspirations investors* are identified on the basis of bonds trading in addition to stocks trading but no derivative assets trading. The subset *Other investors* contains the rest of the population. The monthly turnover is the market value of shares purchased in month t, or sold in month t, divided by the average market value of the portfolio during month t. Panel A presents results for the gross return on a portfolio that mimics the investment of the average investor. Panel B presents results for the gross return on a portfolio that mimics the aggregate investment of all investors. The CAPM intercept is obtained from a time-series regression of the investor excess return on the market excess return. The three-factor intercept is obtained from a time-series regression of investor excess return on the market excess return, a zero-investment book-to-market portfolio and a zero-investment size portfolio. T-stats are presented in parentheses. ***, **, * indicate that results are significant at the 1%, 5% and 10% level.

Table 2.5
Intercept estimates for the subsets based on investors' profile and diversification

	CAPM intercept (%)				Three-factor intercept (%)			
PANEL A: Individual results								
Diversification	**Low**		**High**		**Low**		**High**	
High aspirations investors	-0.873**	(-2.1)	-0.657**	(-2.1)	-1.338***	(-3.1)	-1.044***	(-3.3)
Low aspirations investors	-0.526*	(-1.7)	-0.357*	(-1.7)	-0.730**	(-2.3)	-0.493***	(-2.8)
Other investors	-0.664**	(-2.0)	-0.471**	(-2.0)	-0.928***	(-2.6)	-0.708***	(-2.8)
High aspirations investors - Others	-0.209***	(-3.9)	-0.186***	(-4.7)	-0.410***	(-7.2)	-0.336***	(-8.1)
Low aspirations investors - Others	0.137***	(3.0)	0.114***	(3.5)	0.198***	(4.1)	0.215***	(6.1)
PANEL B: Aggregate results								
Diversification	**Low**		**High**		**Low**		**High**	
High aspirations investors	-0.616	(-1.2)	-0.711**	(-2.0)	-1.180**	(-2.2)	-1.160***	(-3.2)
Low aspirations investors	-0.313	(-0.8)	-0.366	(-1.4)	-0.730*	(-1.8)	-0.446***	(-2.8)
Other investors	-0.314	(-0.9)	-0.471*	(-1.7)	-0.715**	(-2.0)	-0.800***	(-2.8)
High aspirations investors - Others	-0.302***	(-4.9)	-0.240***	(-5.3)	-0.465***	(-7.1)	-0.360***	(-7.6)
Low aspirations investors - Others	0.002	(0.0)	0.105***	(2.7)	-0.015	(-0.3)	0.354***	(8.6)

Percentage monthly returns over the period 1999 to 2006 are computed for the subsets *High aspirations investors*, *Low aspirations investors* and *Other investors* for high (above median) and low (below median) diversification levels. *High aspirations investors* are identified on the basis of derivative asset trading in addition to stocks trading but no bonds trading. *Low aspirations investors* are identified on the basis of bonds trading in addition to stocks trading but no derivative assets trading. The subset *Other investors* contains the rest of the population. Monthly diversification is computed as the number of stocks in portfolio at the start of each month. Panel A presents results for the gross return on a portfolio that mimics the investment of the average investor. Panel B presents results for the gross return on a portfolio that mimics the aggregate investment of all investors. The CAPM intercept is obtained from a time-series regression of the investor excess return on the market excess return. The three-factor intercept is obtained from a time-series regression of investor excess return on the market excess return, a zero-investment book-to-market portfolio and a zero-investment size portfolio. T-stats are presented in parentheses. ***, **, * indicate that results are significant at the 1%, 5% and 10% level.

Chapter 3

Are individual investors really such poor portfolio managers?

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Abstract

This paper evaluates the performance of individual investors through the use of measures that fit their preferences and risk perception. Our study of 24,766 individual investors from a French brokerage between 2003 and 2006 reveals that the choice of alternative performance measures to the Sharpe ratio results in different investor rankings. A larger proportion of investors beat the market index when evaluation is based on a measure that is consistent with their attitude towards risk than when evaluated with the Sharpe ratio. Yet individual investors are seen to underperform a random investing strategy, even when alternative evaluation measures are used. We conclude that the improvement of a given investor's performance when measured with other measures than the Sharpe ratio is driven by mechanical effects linked to the skewness of their portfolio rather than good stock picking skills.

Individual traders are often regarded as at best uninformed, at worst fools. Coval, Hirshleifer, and Shumway (2005).

3.1 Introduction

Financial performance is a major concern for all investors, whether they are professionals or individuals. The success of an investment strategy and the skills of a trader are evaluated ex-post by assigning a score to the portfolio, which usually corresponds to risk-adjusted returns. Global evidence for individual investors shows that they do not outperform relevant benchmarks. Barber and Odean (2000) show that the Jensen's alpha (Jensen, 1968) and the intercept from the Fama-French model (Fama and French, 1993) across a sample of 66,465 U.S. households from 1991 to 1996 were not reliably different from zero. Barber and Odean (2000) also find a Sharpe ratio of 0.179 for the average household in their sample compared to 0.366 for the market during the period (Sharpe, 1966). Using the same two tests, Odean (1999) provides evidence that the stocks bought by investors subsequently underperform compared to the stocks these investors sell. On the Taiwanese market, long-short portfolios that mimic the buy-sell trades of individual investors earn reliably negative monthly alphas of 11.0%, 3.3%, and 1.9% over horizons of 1, 10, and 25 days respectively (Barber, Lee, Liu, and Odean, 2009).

Research demonstrates that these poor results can be explained by various psychological considerations, including overconfidence, familiarity bias, or loss aversion. Even if these considerations are unrelated to the information about underlying security values, they impact the trading choices of individual investors. As a result, individual investors trade excessively, under-diversify their portfolio and have a tendency to sell winners too early and to ride losers too long (the so-called disposition effect).

In this paper, we argue that the poor performance of individual investors may simply be explained by the use of an ill-suited performance measure. Indeed, in risk-adjusted return indicators such as Jensen's alpha, Fama-French intercept and the four-factor intercept, risk is defined by the variance of the outcomes. However, surveys reveal that the variance does not fit with the risk perception of individual investors (Unser, 2000; Veld and Veld-Merkoulova, 2008). Therefore, although these performance indexes are widespread in the literature, we should interpret them cautiously when they are related to individual investors. The same argument applies to the Sharpe ratio, one of the most popular performance measure in the finance industry. In "The (more than) 100 ways to measure portfolio performance" Cogneau and Hubner (2009a) and Cogneau and Hubner (2009b) suggest that a number of alternative performance measures overcome the main drawbacks of the Sharpe ratio. Besides the abovementioned problem of risk perception, the fact that the Sharpe ratio stem from the Expected Utility Theory (EUT) makes its use questionable as a relevant performance measure for individual investors. Although the EUT implies that investors exhibit a uniform attitude towards risk (i.e, they are risk averse or risk seeking throug hout), (Von Neumann and Morgenstern, 1947), experimental evidence shows that investors do not behave this way. Research has established that individual investors exhibit loss aversion, have risk-averse preferences for gains combined with risk-seeking preferences for losses[1] (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992) and target lottery-like outcomes (Friedman and Savage, 1948; Mitton and Vorkink, 2007). To address these behaviors, the Prospect Theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992) and the Behavioral Portfolio Theory (BPT) (Shefrin and Statman, 2000) have been proposed as alternative models of preferences.

In this study, we demonstrate that individual investors are not such poor managers when their performance is evaluated using measures that correctly weight their preferences and risk perception. More precisely, we select performance measures which adjust gains by the risk associated with losses (downside risk) rather than the total risk. Furthermore we allow for different models of choices through the use of Farinellis performance measure (Farinelli and Tibiletti, 2008). This ratio exhibits a great flexibility, thus permitting us to weight attitude toward risk for gains and losses.

Our empirical study shows that when the performance measure is consistent with the Behavioral Portfolio Theory, the proportion of individual investors beating the market is much higher than the proportion obtained using the Sharpe ratio. As a consequence, we highly recommend the replacement of the Sharpe ratio by performance measures that are better tailored to evaluate the performance of individual investors.

[1] This is the certainty effect (risk-averse preference for a sure gain over a larger gain that is merely probable) combined with the reflection effect (risk-seeking preference for a loss that is merely probable over a smaller losses that is certain).

The equivalence of performance measures is a topic of debate in the literature. On the one hand, Eling and Schuhmacher (2007) compare 13 performance measures[2] and do not find them to significantly affect the ranking of 2763 hedge funds (over the period 1985-2004) in any way. In fact, the average rank correlation of performance measure with the Sharpe ratio is 97%. Eling (2008) confirms these results on a set of 38,954 mutual funds invested in stocks, bonds, commodities and real estate. On the other hand, Zakamouline (2011) finds that the evaluation of performance very much depends on the choice of performance measure.

Our study contributes to existing literature on alternative performance measures by focusing on individual investors rather than hedge funds. Our contribution is threefold. Firstly, our results support those of Zakamouline (2011). We find that the choice of alternative performance measures does indeed have an impact on investor ranking. For instance, the proportion of investors who are upgraded (downgraded) in 2003 through another measure than the Sharpe ratio ranges from 35.94% to 46.45% (5.85% to 36.19%). We show that these proportions differ significantly from what is expected with random permutations.

Secondly, we show that individual investors are not such poor managers as the Sharpe ratio ranking reports when their performances are compared to the market index. For example, though only 10% of investors outperformed the market index

[2] Sharpe ratio, Treynor ratio, Jensens alpha, Omega ratio, Sortino ratio, Kappa3 ratio, Upside Potential ratio, Calmar ratio, Sterling ratio, Burke ratio, Excess return on value at risk, Conditional Sharpe ratio and Modified Sharpe ratio.

in 2006 according to the Sharpe ratio, 60% of the population beat the market when evaluated with the measure fitting the Behavioral Portfolio Theory. With this measure, 30% of investors outperform the market during 4 consecutive years, whereas no investor beats the market persistently with the Sharpe ratio. Finally we show that randomly created portfolios outperform those of investors in our sample, even with the alternative measures. We conclude that improvements in investors' performances are not driven by their stock-picking skills, but rather by mechanical effects linked to the skewness of their portfolio as a whole. As a result, though our main finding is the importance of choosing the correct measure, we do not conclude that individual investors exhibit particular skills to select outperforming stocks.

This paper is organized as follows: In Section 1, we challenge the Sharpe ratio and present the alternative measures analyzed in our study. We present the empirical study in Section 2 and we conclude in Section 3.

3.2 The Sharpe ratio and the alternative measures

The Sharpe ratio is usually computed as follows

$$Sharpe\, ratio = \frac{(r_i - r_f)}{\sigma_i} \tag{3.1}$$

in which r_i is the mean return of the investor i, r_f is the risk free rate and σ_i is the standard deviation of the portfolio returns. Although this measure has a simple design and includes the two main elements of risk and return, it is not an appropriate tool for evaluating the performance of individual investors.

It is inadequate for two reasons. Firstly, it is impossible to establish a global ranking of investors with the Sharpe ratio. Indeed, when the numerator is positive, the higher the excess return and the lower the standard deviation, the larger the Sharpe ratio will be. However in case of a negative numerator, investors cannot be ranked in order of their performance. The following example illustrates this limitation with assets A ($r_A - r_f = -0.10; \sigma_A = 0.40$), B ($r_B - r_f = -0.10; \sigma_B = 0.50$), and C ($r_C - r_f = -0.05; \sigma_C = 0.40$).

$$Sharpe\, ratio_A = \frac{(r_A - r_f)}{\sigma_A} = -0.25$$

$$Sharpe\, ratio_B = \frac{(r_B - r_f)}{\sigma_B} = -0.20$$

$$Sharpe\, ratio_C = \frac{(r_C - r_f)}{\sigma_C} = -0.125$$

A and B exhibit the same excess return, but B is more volatile. A is therefore, preferred to B. In terms of Sharpe ratio, this means that $Sharpe\, ratio_B = -0.20$ is worse than $Sharpe\, ratio_A = -0.25$. In this case, the lower the Sharpe ratio, the better the asset performance will be. However, if we compare A and C, which exhibit the same volatility, but $r_C = -0.05$ is larger than $r_A = -0.10$. C is therefore preferred to A, meaning that $Sharpe\, ratio_C = -0.125$ is better than $Sharpe\, ratio_A = -0.25$. Here, the rule is reversed: the higher the Sharpe ratio, the better the asset performance will be.

Secondly, the variance used as a risk measure in the Sharpe ratio constitutes a major drawback because it allocates the same weight to positive and negative deviations. Surveys on risk perceptions reveal that symmetric risk measures are actually neglected by investors in favour of asymmetric ones (Unser, 2000; Veld and Veld-Merkoulova, 2008).

At the same time, Ang and Chen (2006) show that returns integrate a premium for the risk of losses. The disappointment associated with the experience of losing a sum of money appears to be greater than the pleasure associated with gaining the same amount; this effect is called "loss aversion" (Kahneman and Tversky, 1979; Kahneman, Knetsch, and Thaler, 1990; Tversky and Kahneman, 1992).

Numerous alternative measures to the Sharpe ratio have been suggested in the literature. In this paper, we study alternative measures that have a *return/risk* design. This simplicity is the one main strength of the Sharpe ratio. To address the abovementioned weaknesses, we have selected alternative measures that are based on upper and lower partial moments.

Lower partial moments (LPM) measure the risk as negative deviations from a reference point. Therefore, they evaluate undesirable volatility (i.e., left-side volatility), or the so-called "downside risk". The lower partial moment of order k ($k > 0$) for investor i during the period T is defined as

$$LPM_k(r_i) = \frac{1}{T}\sum_{t=1}^{T}[Max(0, \tau - r_{it})]^k \tag{3.2}$$

in which τ is the target return and r_{it} is the stock return on date t. The coefficient k weights the deviation from the target return. For example, the LPM of order one measures the expected value of loss, and the LPM of order two measures the semi-variance. Note that semi-variance is a measure for the asymmetry of the distribution. In the case of symmetric returns, the semi-variance is equal to half of the variance.

In the LPM of order k, if $k > 1$, the greater the value of k, the higher the emphasis on the extreme deviations from the benchmark will be. In contrast, a $k < 1$ means that the agents main concern is to fail the target without regard to the amount lost. If moderate deviations from the target are relatively harmless when compared to large deviations, then a high order for the lower moment is adapted ($k > 1$). Figure 3.1 illustrates this mechanism. For each graph, returns r_{it} presented on the x-axis lie between -2% and 2%. Outcomes $[Max(0, \tau - r_{it})]^k$ based on a target return equal to 0.5%, are on the y-axis. We present 2 cases for k: $k = 0.5$ and $k = 1.5$. For $k < 1$, each additional percent of return *lost* provides a diminishing marginal contribution to the outcome. By contrast, when $k > 1$, each additional percent of return *lost* results in an increasing marginal contribution to the outcome.

Symmetrically to Lower Partial Moments, Upper Partial Moments (UPM) measure the positive deviation of returns from the target return

$$UPM_k(r_i) = \frac{1}{T}\sum_{t=1}^{T}[Max(0, r_{it} - \tau)]^k \tag{3.3}$$

As for lower partial moments, the coefficient k ($k > 0$) enables the user to allocate a weight to deviations (see figure 3.2). The higher the order, the higher the agents inclination towards the extreme outcomes will be (with outcomes equal to $[Max(0, r_{it} - \tau)]^k$). If small gains are satisfactory, then an order lower than 1 fits the purpose ($k < 1$).

Partial moments are therefore always positive, allowing a global ranking of investors. Risk is defined by downside risk, and loss aversion can be taken into account by using a higher coefficient for lower moments than upper moments.

The Farinelli-Tibiletti ratio is a performance measure based on Upper Partial Moments at the numerator and Lower Partial Moments at the denominator

$$Farinelli - Tibiletti_{(p-q)} \quad ratio(r_i) = \frac{(UPM_p(r_i))^{1/p}}{(LPM_q(r_i))^{1/q}} \tag{3.4}$$

The flexibility in the coefficients p and q makes it possible to design a performance measure adapted to investor preferences.

In a first case, we choose p and q values equal to 1 to convey neutral attitude towards risk for gains and losses. Indeed, $p = q = 1$ implies that positive and negative deviations from the target are equally weighted. The Farinelli-Tibiletti$_{(1,1)}$ corresponds to the Omega ratio, previously proposed by Keating and Shadwick (2002).

$$Omega\, ratio(r_i) = \frac{(UPM_1(r_i))}{(LPM_1(r_i))} \tag{3.5}$$

In a second case, we include loss aversion in the Farinelli-Tibiletti ratio, with a higher order for the LPM: $q = 2$. The Farinelli-Tibiletti$_{(1,2)}$ corresponds to the Upside Potential ratio, previously proposed by Sortino, Van Ver Meer, and Plantinga

(1999).

$$Upside\,potential\,ratio(r_i) = \frac{(UPM_1(r_i))}{(LPM_2(r_i))^{1/2}} \tag{3.6}$$

The Omega ratio and the Upside Potential ratio are the first measures selected for comparison to the Sharpe ratio in our study (selected performance measures are summarized in table 3.1).

The Sharpe ratio microeconomic foundations stem from the Expected Utility Theory (EUT)(Von Neumann and Morgenstern (1947)). A performance measure that is suited to this model reflects risk aversion in the separate domains of gains and losses. To take this type of behaviors into account, we choose $p < 1$ and $q > 1$. Indeed, in the domain of gains (UPM at the numerator), $p < 1$ indicates that investors are not necessarily seeking large gains with low probability of occurrence. Instead, they are satisfied as soon as outcomes exceed the target and additional gains provide a decreasing marginal contribution to utility. In the domain of losses (LPM at the denominator), $q > 1$ signifies that large deviations from the target return are not desired, and the marginal contribution of additional losses to utility increases.

In the Expected Utility Theory, investors exhibit uniform attitude towards risk. However, Kahneman and Tversky (1979) evidence the inability of the EUT to explain investor portfolio choices. More precisely, their study has provided experimental evidence of a fourfold pattern of risk attitudes: risk aversion for most gains and low probable losses, and risk-seeking for most losses and low probable gains.

To consider the attitude towards risk for most commons events, Kahneman and Tversky (1979) introduced a S-shaped utility function (the so-called Value function) in Prospect Theory. With this Value function, the marginal value of both gains and losses decreases with their magnitude. The concept of loss aversion is taken into consideration by using a steeper Value function for losses than for gains. We take this model of preferences into account in the Farinelli-Tibiletti ratio with $p < 1$ at the numerator, meaning that the investor is risk-averse in the domain of gains, and $q < 1$ at the denominator, meaning that the investor is risk-seeking in the domain of losses.

Concerning unlikeky outcomes, Kahneman and Tversky (1979) report that individuals are risk-averse for losses and risk-seeking for gains. This behavior is in line with Friedman and Savage (1948)'s puzzle, namely that investors who buy insurance policies often buy lottery tickets at the same time. Friedman and Savage (1948) explain that (p.279) *"An individual who buys fire insurance on a house he owns is accepting the certain loss of a small sum (the insurance premium) in preference to the combination of a small chance of a much larger loss (the value of the house) and a large chance of no loss. That is, he is choosing certainty in preference to uncertainty. An individual who buys a lottery ticket is subjecting himself to a large chance of losing a small amount (the price of the lottery ticket) plus a small chance of winning a large amount (a prize) in preference to avoiding both risks. He is choosing uncertainty in preference to certainty"*.

More recently, researchers observe that individual investors design their portfolio with the intention of increasing the likelihood of extremely positive returns. In other words, investors make the distribution of their wealth more lottery-like (Statman, 2002; Kumar, 2009; Barberis and Huang, 2008). Kumar (2009) define lottery-type stocks following the salient features of state lotteries. Lottery tickets have very low prices relative to the highest potential payoff (i.e., the size of the jackpot); they have low negative expected returns; their payoffs are very risky (i.e., the prize distribution has extremely high variance); and, most importantly, they have an extremely small probability of a huge reward (i.e., they have positively skewed payoffs). As with lotteries, if investors are searching for lottery-like assets, they are likely to seek low-priced, high stock-specific skewness stocks.

Along the same lines, Mitton and Vorkink (2007) find that investors deliberately hold few stocks to capture positive skewness. Indeed, though increasing the number of assets in a portfolio makes it possible to decrease the total variance by cancelling the specific risk of each security, it also reduces portfolio skewness. Therefore, a strategic underdiversification is necessary to capture asymmetric returns. Moreover, underdiversified investors are more prone to select positively skewed stocks (Mitton and Vorkink, 2007). Goetzmann and Kumar (2008) shows that investors who tilt their portfolio towards stocks with an asymmetric distribution and a high variance (small capitalizations, growth stocks, technological sector) hold concentrated portfolios.

Shefrin and Statman (2000)have emphasized the role of gambling in investment decisions in their Behavioral Portfolio Theory (BPT). According to BPT, investors proceed in two steps to set their portfolio. First they satisfy a security criterion, ensuring a minimum return with riskless assets. Then they invest their remaining wealth in a cheap asset with a huge probability of gains.[3]

In Prospect Theory, BPT preferences can be addressed by the combination of the Value function and an overweighting of the probabilities of extreme events. The probability transformation offsets the initial shape of the Value function. As a result, each additional percent of return lost provides decreasing marginal contribution to disutility, whereas each additional percent of return gained provides increasing marginal contribution to utility. We can reflect such attitude in the Farinelli-Tibiletti ratio with $p > 1$ at the numerator and $q > 1$ at the denominator. With $p > 1$, investors target exceptional performances and attach importance to large but unlikely excess returns above the benchmark. $q > 1$ means that large losses are undesired.

In that paper, we follow Zakamouline (2011) and estimate the Farinelli-Tibiletti ratio according to 3 $(p - q)$ pairs: $(0.5 - 2)$ to be in accordance with the EUT; $(0.8 - 0.85)$ to model the Value function, and $(1.5 - 2)$ to depict BPT investors.

To sum up, alternative performance measures are always positive and consider downside risk using lower partial moments at the denominator. The Omega ratio represents investors with neutral attitude towards risk. The Upside Potential ratio takes loss aversion into consideration with the use of a stronger coefficient for LPM. The Farinelli-Tibiletti ratio$_{(0.5\text{-}2)}$ represents investors who behave as it is assumed in the EUT, the Farinelli-Tibiletti ratio$_{(0.8\text{-}0.85)}$ represents investors whose preferences are conveyed by the Value function and the Farinelli-Tibiletti ratio$_{(1.5\text{-}2)}$ represents

[3]Two versions of BPT co-exist: One mental account and multiple mental accounts. We use the one mental account case.

investors who behave accordingly with the BPT.

This first section explains why the Sharpe ratio is not a suitable measure to estimate the performance of individual investors. Based on five alternative performance measures that overcome the Sharpe ratio main drawbacks, we will now evidence that the evaluation of individual performance is influenced by the choice of the measure. In a second step, we show that investors are not such poor managers when their performances are evaluated using alternative measures.

3.3 Empirical study

3.3.1 Data

The primary data set is provided by a large European brokerage house, and is composed of the daily transactions records of 24,766 French investors over the period 2003-2006. Descriptive statistics related to these investors are presented in table 3.2. Data in panel A indicate that among the 24,766 investors, 80.4% are men. Panels B and C are dedicated to transactions and portfolios respectively, and present yearly results. The 24,766 investors executed 1,882,044 transactions over the 4 years. On average, each investor executed 19.2 transactions in 2003, 16.7 transactions in 2004, 18.7 transactions in 2005 and 21.4 in 2006. The investors average purchase (sale) turnover lies between 5.9% (6.2%) in 2004 and 7.8% (8.7%) in 2006. Note that the purchase turnover and the sales turnover are the values of the amounts bought or sold, respectively, as a proportion of the monthly portfolio value.

The calculation of each investors daily stock portfolio using the trade records reveals an average value of 24,241 euros in 2003, 27,901 euros in 2004, 31,259 euros in 2005 and 36,629 euros in 2006, with investors holding an average of 8 stocks in their portfolios. Yearly returns of portfolios are computed based on weekly returns. The lowest annual return is observed in 2004 (8.16%) whereas the highest is observed in 2003 (31.40%). Over the same period, the market index exhibits annual returns of 22.99% (2003), 14.95% (2004), 28.99% (2005) and 25.23% (2006).[4] The difference between the average return of investors and the market return in 2003 is explained by an important skewness of investors' portfolios (0.76). Computed Jensen's α values are consistent with these differences. Indeed, in 2003, α is positive, equal to 6.99% whereas in 2004 it is negative, equal to -3.83%.

It is worth mentioning that in 2003 (resp. 2004, 2005, 2006), 82.8% (resp.18%, 37.7%, 44.5%) of investors hold portfolio with non-Gaussian distribution of returns. We test normality with the Jarque-Bera test at 95% confidence level.

Stock price data come from two sources, Eurofidai for stocks traded on Euronext and Bloomberg for the other stocks. Investors trade 2,491 stocks, of which 1,191 are French, and the vast majority of the remaining stocks comes essentially from the U.S. (1020 stocks). Despite this large proportion of U.S stocks, more than 90% of transactions are carried out on French stocks.

[4]Data on the market index is given by the Eurofidai general index (computed using the methodology of the Center for Research in Security Prices, CRSP, and based on approximately 700 stocks over the period under consideration). European financial data institute: https://www.eurofidai.org

In the following section, we demonstrate that the alternative measures chosen in this study are not equivalent to the Sharpe ratio. This observation is the starting point required to justify that alternative measures should be favored over the Sharpe ratio when evaluating individual investors.

3.3.2 Equivalence between measures

Two measures are considered equivalent if they generate the same ranking of investors. Performance measures are calculated each year using weekly returns. The target return on performance measures requiring such target return is the risk-free rate. Each year, we sort investors into deciles with each measure, including the Sharpe ratio.

The Sharpe ratio is computed using two variables (average return and standard deviation) which summarize the return distribution of an investor's portfolio. Before ranking investors based on the value of their portfolio's Sharpe ratio, it is necessary to test whether this measure is representative of the return distribution with a bootstrap on returns. For each investor, we create 1,000 distributions of 52 returns that have been randomly selected amongst the actual distribution of portfolio returns. The Sharpe ratio is calculated for each distribution created. We thus obtain a confidence interval for the measure. Our tests show that the Sharpe ratio of each investor is comprised in its 95% confidence level. We conclude that the Sharpe ratios computed in this study are not due to chance.

This test is not required for the alternative measures which are computed using each return that makes up the distribution.

The ranking computed for the Sharpe ratio is slightly different from a classic ranking. Although we cannot rank several investors who exhibit a negative Sharpe ratio together, we can rank a positive and a negative Sharpe ratio. Indeed, the positive Sharpe ratio is better than the negative one. We thus rank investors who exhibit a negative Sharpe ratio in the bottom decile. It follows that the bottom decile may contain more than 10% of investors. More precisely, in 2003 (resp. 2004 2005 and 2006), the bottom decile contains 4.22% (resp. 25.85%, 7.52% and 8.57%) of investors. We then rank investors who exhibit a positive Sharpe ratio in nine quantiles. Each of these nine quantiles contains 11.11% of the remaining investors.

We present the rank correlations in table 3.3. We compute two statistics (Spearman ρ and Kendall τ) and both result in similar conclusions, although the Kendall τ provides lower statistics. Since both statistics are supported by researchers in the literature (Noether, 1981; Griffiths, 1980), there is no reason to prefer one to the other.

The Omega ratio is the measure that exhibits the higher correlation with the Sharpe ratio. With the Spearman rho, the correlation is close to 98% each year. Therefore, the mere consideration of the downside risk does not modify the evaluation of investors. The Upside Potential ratio is the second most correlated measure with the Sharpe ratio. Including loss aversion does not substantially influence the evaluation of investors. We observe that the correlation is stronger in 2004, when the proportion of investors exhibiting normal returns is the highest (82%). This correlation rises to 94.88% with the Spearman statistic. Since the alternative measures are based on deviations from the benchmark, the ranking by these measures should be closer to the ranking produced by the Sharpe ratio when returns are normal. Yet we do not observe a similar increase of correlation with the other measures, indicating that others effects are interacting.

In order of decreasing correlation, we next find the Farinelli-Tibiletti(0.5-2) ratio and the Farinelli-Tibiletti(0.8-0.85) ratio which exhibit similar strentgh of relationship with the Sharpe ratio. Both ratios assume risk aversion for gains. Lastly, we observe the lowest correlation with the Farinelli-Tibiletti(1.5-2) ratio. For the latter, Spearman ρ ranges between 30.59% and 41.58%, and Kendall τ ranges between 23.17% and 32.60% across years. This is the only measure which conveys risk-seeking for gains.

These strengths of relationship between alternative measures and the Sharpe ratio are corroborated by the transition matrices presented in tables 3.4, 3.5, 3.6, 3.7 and 3.8. The rows present the ranking that results from the evaluation of investors' performance with the Sharpe ratio. The columns present the ranking that results from evaluation via the considered alternative measure. For each pair of deciles (i, j), we report the conditional probability to be ranked in decile j with the alternative measure when the rank with the Sharpe ratio is decile i. [5]

If the rankings are similar, i.e., the decile of investor with the Sharpe ratio (i)

[5]Based on contingency tables (i.e., the observed frequencies for each pair of deciles (i, j)), Khi2 test confirms that the ranking of investors according to the Sharpe ratio is not independent from the ranking of investors according to alternative measures: $P(i, j) \neq P(Decile_{Sharpe} = i) * P(Decile_{Alternative\,Measure} = j)$.

and the decile of investor with the alternative measure (j) are equal, we should only observe positive probabilities on the main diagonal of the matrix.

We see clearly that the rankings resulting from the evaluation of performance with the Omega ratio and the Sharpe ratio are close. Indeed, most probabilities in the matrices are null except the values on the main diagonal where $i = j$ and on the second diagonals where $j = i+1$ and $j = i-1$. For instance in 2003, if an investor is ranked in the first decile with the Sharpe ratio, then the probability of being ranked in the first decile with the Omega ratio is 100%. Therefore the probability to be in $j = 2, ..., 10$ is null when $i = 1$. If the investor is ranked in decile i with the Sharpe ratio, then there are high probabilities that he will be ranked in $j = i$ or in decile $j = i - 1$ with the Omega ratio. Similar patterns are observed for 2005 and 2006. Yet in 2004, the diagonal shifts to the right of the matrix. Hence, there is a higher probability that an investor ranked in decile i ($i = 3\, to\, 8$) with the Sharpe ratio will be ranked in decile $j = i + 1$ than in decile $j = i$ when evaluated with the Omega ratio. With the Upside potential ratio, the conditional probabilities are spread more widely across the matrices, but they are null for the extreme pairs of deciles. For instance, in 2004 with $i = 10$, we observe null probabilities for $j = 1$ to $j = 4$, i.e. an investor ranked in the top decile with the Sharpe ratio cannot be ranked in the first (i.e. least performant) deciles with the Upside potential ratio. We obtain even more positive conditional probabilities with the Farinelli-Tibiletti$_{(0.5\text{-}2)}$ and the Farinelli-Tibiletti$_{(0.8\text{-}0.85)}$.

With the Farinelli-Tibiletti$_{(1.5\text{-}2)}$ ratio, the conditional probabilities are spread across the whole matrix. In other words, it is possible to be ranked in each $j = 1, ..., 10$

resulting from the alternative measure evaluation, whatever the decile i resulting from the Sharpe ratio evaluation. We observe similar patterns across years.

These transition matrices indicate that the choice of performance measure does influence the evaluation of investors, hence corroborating Zakamouline (2011)' works. We summarize the rank permutations in table 3.9. With the Farinelli-Tibiletti(1.5-2) ratio, the maximum downgrade (presented in column 1) is -9. In other words, some investors ranked in the best decile with the Sharpe measure move to the bottom decile with this alternative measure. We observe the same phenomenon in the opposite direction. For instance, in 2003, when the 3 versions of the Farinelli-Tibiletti ratio are used, the maximum upgrade (presented in column 2) is 9. With the Omega ratio the maximum upgrade is 2 in 2003 and 2005, and only 1 in 2004 and 2006. Note that the maximum upgrade is always observed with the Farinelli-Tibiletti(1.5-2) ratio, ratio, which is consistent with the fullness of the transition matrices. We observe that the results are similar for the Upside Potential ratio that takes loss aversion into consideration and the Farinelli-Tibiletti(0.5-2) ratio that accounts for the Expected Utility Theory.

We present the proportion of investors who remains in the same decile in the third column. In 2006 for instance, this proportion ranges from 17.90% with the Farinelli-Tibiletti(1.5-2) ratio to 82.64% with the Omega ratio. Over the years, the highest proportion of investors who remain in the same decile is always observed with the Omega ratio, followed by the Upside potential ratio. By contrast, the largest proportions of investors who move to a higher/lower decile (see the fourth and fifth column of the table) are observed with the Farinelli-Tibiletti$_{(1.5\text{-}2)}$ ratio. In 2004, this measure shows 47.33% of investors to be downgraded whereas 36.27% of investors are upgraded.

Hence, a considerable proportion of investors moves to a different decile with certain alternative measures. Computed proportions are similar across years, supporting the robustness of this observation.

To test whether these rank permutations are significant, we run Monte-Carlo simulations. More precisely, we create a vector of 24,766 fictitious investors, ranked in deciles. We rank investors #1 to #2477 in the first decile, investors #2478 to #4955 in the second decile, and so on through to investors $\#22,290$ to $\#24,766$ who are ranked in the 10^{th} decile. Based on this initial vector, we compute 1,000 random rank permutations to obtain 1,000 new vectors with permuted deciles. Across the 1,000 permutations, the proportion of fictitious investors remaining in the same decile ranges between 9.63% and 10.38% at the 95% confidence level. If our results were driven by chance, the proportion of investors who remain in the same decile when we evaluate them with an alternative measure rather than with the Sharpe ratio should therefore be comprised within this confidence interval. Yet if we take the example of 2003, the actual proportions ranges from 17.35% to 58.20%. The permutations that we observe are therefore not the result of a random process.

3.3.3 Comparison with the market index

Permutations resulting from evaluation with alternative measures also apply to the market index. In table 3.10 we present the decile of the market index, for each year and each measure. These grades are based on the initial investor ranking computed for each measure. To understand how the choice of performance measure influences the investor evaluation, it is interesting to analyze this table in term of percentages. For example, in 2005, only 10% of investors outperform the market index according to the Sharpe ratio. Yet, if we refer to the Farinelli-Tibiletti$_{(0.8\text{-}0.85)}$ ratio for the same year, 30% of investors beat the market, whilst this proportion rises to 60% with the Farinelli-Tibiletti$_{(1.5\text{-}2)}$ ratio. Therefore, evaluating investors with a measure that fits the S-shaped Value function leads to worse results (for investors) than with a measure that fits the Behavioral Portfolio Theory. This is even more evident in 2004: although a mere 10% of investors outperform the market index according to the Sharpe ratio, 90% of the population is ranked in a better decile when evaluated with the Farinelli-Tibiletti$_{(1.5\text{-}2)}$. This large difference is consistent with the results reported in table 3.9 and leads us to wonder whether individual investors are really such poor managers as studies usually report. Note that the measure that fits the Value function in Prospect Theory is the second most favorable measure for individual investors. In 2003, we observe a smaller difference between the ranks defined according to each measure. This effect is consistent with the strong outperformance of the annual returns of investors on the market this particular year (see table 3.2).

To test whether our results are driven by the value of p and q chosen in that paper, we compute the proportion of investors who beat the market each year, according to the value of $(p - q)$ coefficients.

Results are presented in figure 3.3, 3.4, 3.5 and 3.6. p and q coefficients lie between 0 and 4, with a 0.1 incremental unit. It appears that the proportion of investor who beat the market increases with the coefficient p and q.

Depending on the value of $(p-q)$, the proportion of investors who beat the market ranges between 10 % and 90% in 2003, and between 0% and 90% in 2004. In 2005 and 2006, the maximum proportion of investors who beat the market is 70%.

To end up with the largest proportion of investors beating the market (darkest area) when $q = 2$, p value must be at least equal to 1.5 in 2003, 1.3 in 2004, and 2 in 2005. These results explain why the Farinelli-Tibiletti$_{(1.5\text{-}2)}$ ratio gives rise to a larger part of investors beating the market than the Farinelli-Tibiletti$_{(0.5\text{-}2)}$. In 2006, if $q = 2$, the value of p must be at least 3.9 in order to be located in the darkest area. This value is more than twice the highest p value in our computations ($p = 1.5$). Our observation is consistent with the previous result that only 50% of investors beat the market with the Farinelli-Tibiletti$_{(1.5\text{-}2)}$ in 2006. In fact, with $q = 2$, the proportion of investors who beat the market increases with the value of p. The surface is darker and darker as we move towards the right-hand side of the figure.

If we compare $p = 0.5$ and $p = 0.8$, the proportion of investors who beat the market is usually higher with $p = 0.8$, whatever the value of q. The value of p (for the UPM at the numerator) is therefore more determinant than the value of q (for the LPM at the denominator) when evaluating the outperformance of investors.

We next examine whether outperformance is persistent over time. In table 3.11, we present the proportion of investors who are ranked in a higher decile than the market index with each measure over 1, 2, 3 and 4 years from 2003 onwards. In other words, we analyze the proportion of investors who beat the market in 2003, in 2003 and 2004, in 2003, 2004 and 2005 and in 2003, 2004, 2005 and 2006. With the Farinelli-Tibiletti$_{(1.5\text{-}2)}$ ratio, 90% (resp. 81.37%, 48.16%, 30.48%) of investors beat the market over 1 year (2 years, 3 years, 4 years, respectively). These are the largest proportions in the table, followed by the values obtained with the Farinelli-Tibiletti$_{(0.8\text{-}0.85)}$ ratio and the Farinelli-Tibiletti$_{(0.5\text{-}2)}$ ratio. This can be compared with results using the Sharpe ratio, in which 42.66% of investors beat the market in 2003, 4.67% in 2003 and 2004, 1.12% from 2003 to 2005 and less than 0.3% over the complete period.

Therefore, we conclude that a handful of them persistently beat the market when evaluated with the Sharpe ratio. By contrast with the measure that fits BPT, more than a quarter of investors beat the market over 4 consecutive years.

3.3.4 Skills or luck?

In the previous section, we provided evidence that the Farinelli-Tibiletti$_{(1.5\text{-}2)}$ ratio, which is consistent with the Behavioral Portfolio Theory, promotes the portfolio held by individual investors. In other words, individual investors perform much better with this measure than with the others. BPT investors tend to increase the likelihood of extreme positive returns by making the distributions of their wealth more lottery-like. Mitton and Vorkink (2007) show that this skewness-seeking drives investors to hold under-diversified portfolios. Consistent with this finding, the median number of stocks held in portfolio is 6 in our sample (see descriptive statistics in table 3.2). According to Statman (1987), a well-diversified portfolio must include at least 30 stocks. Hence, investors hold under-diversified portfolios, which implies that the distribution of returns in their portfolios is asymmetric. Both results (outperformance of investors with BPT and underdiversification) jointly indicate that the behavior of investors is best modelized with the Behavioral Portfolio Theory.

In this section we analyze whether the observed outperformance of investors is solely mechanical. Actually, it is not surprising to find that investors who are under-diversified outperform the market with a measure that promotes asymmetric returns. Though our results might be purely driven by mechanical effects, our goal in this paper is to emphasize that there are more suitable measures to evaluate individual investors than the Sharpe ratio. We indeed show that these measures lead to detailed conclusions concerning the poor trading ability of investors. However, can we really conclude that individual investors select stocks correctly? Do they really have particular stock picking skills? Are their results any better than those they could achieve by luck ?

To answer these questions, we start with the creation of 24,766 portfolios composed of randomly picked stocks. The weights that we allocate to each stock in the portfolios are also drawn randomly. We then compute Sharpe ratios and alternative measures each year, for each portfolio, based on weekly returns. Lastly, we rank the random portfolios using each measure for every year in question. The number of stocks in each portfolio mimics the number of stocks of investors. More precisely, the first portfolio created contains exactly the same number of stocks than the portfolio of the investor #1; The second portfolio created contains exactly the same number of stocks as the portfolio of investor #2; and so on.

We then analyze the rank of the market index among these random portfolios. As table 3.12 shows, with the 3 versions of the Farinelli-Tibiletti ratio, the market index is in the bottom part of the ranking each year. In other words, 90% of the random portfolios outperform the market index. Comparing this large proportion with the results reported in table 3.10, we remark that investors do not perform better than the randomly chosen portfolios.

Though the Farinelli-Tibiletti ratio enhances investor performance, it promotes an under-diversified random strategy even more. Interestingly, the random strategy is promoted by the measures that fit the 3 models of decision making considered in our study. Although the Farinelli-Tibiletti$_{(1.5\text{-}2)}$ ratio promotes positive skewness, the opposite is seen for the Farinelli-Tibiletti$_{(0.5\text{-}2)}$ ratio. Indeed, the Expected Utility Theory penalizes any deviations from the target return that arise due to a lack of diversification. We assume that the good performance of randomly selected stocks overcomes this effect. Consequently, it is the shape of portfolio return distribution which boosts investor performance. The overall increase in performance is not due to the particular stocks chosen.

With the Sharpe ratio, the Omega ratio, and the Upside potential ratio, the market index is, as expected, in the top of the ranking. Yet in 2003, although the index is ranked in higher deciles with these measures in comparison with the Farinelli-Tibiletti ratios, the outperformance is not so clear. Indeed, at least 60% of the randomly created portfolios are ranked in a better decile. We observed a similar effect with the investor portfolios (see table 3.10).

3.4 Conclusions

In this paper we compare the evaluation of performances resulting from the Sharpe ratio with those resulting from alternative performance measures. We consider five measures designed on the same basis as the Sharpe ratio (return to risk ratio). These measures are always positive and enable a ranking among investors in all cases, whereas the Sharpe ratio is meaningless when negative. Besides this main difference, risk is defined by negative deviation from a target, rather than by the variance.

Alternative measures are built with partial moments and are designed to take several preferences of investors into consideration. The Omega ratio represents neutral attitude towards risk for gains and losses. The Upside Potential ratio incorporates the concept of loss aversion with a stronger weight allocated to losses than to gains. Investors within the Expected Utility Theory, who are risk-averse throughout, are considered with the Farinelli-Tibiletti$_{(0.5\text{-}2)}$ ratio. Investors whose preferences are consistent with the Value function in the Prospect Theory (i.e., risk-averse for gains and risk-seeking for losses) are represented in the Farinelli-Tibiletti$_{(0.8\text{-}0.85)}$ ratio. Lastly, investors who behave as it is assumed in the Behavioral Portfolio Theory (i.e., risk-seeking for gains and risk-averse for losses) are taken into consideration with the Farinelli-Tibiletti(1.5-2) ratio. Considering the tendency to seek skewness through under-diversification reported by Mitton and Vorkink (2007), this seems to be the best-fitting model for the behavior of individual investors.

We first show that the choice of performance measure does influence the ranking of investors. Indeed, a significant proportion of investors moves to a higher/lower decile when we estimate their performance with an alternative measure. Second, we find that a greater proportion of investors outperform the market index with alternative measures, notably with the Farinelli-Tibiletti(1.5-2) ratio. Furthermore, 30% of investors persistently beat the market (over 4 consecutive years) with the Farinelli-Tibiletti(1.5-2), compared to 0.3% with the Sharpe ratio.

Hence estimating performance with a measure that correctly weights the skewness of investor portfolios provides evidence that their risk-adjusted returns are far better than usually reported with performance measures stemming from the Mean-Variance framework. We do however find that the improvement of portfolio performance when evaluated with alternative measures is mainly due to mechanical effects due to skewness rather than stock-picking skills. Indeed, individual investors are seen to underperform a random investing strategy even when they are evaluated with adequate alternative measures.

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Figure 3.1
Lower Partial Moments

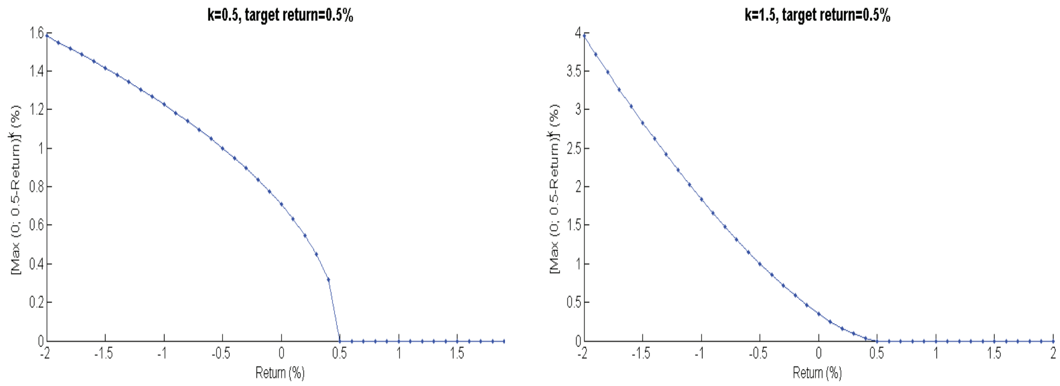

Figure 3.2
Upper Partial Moments

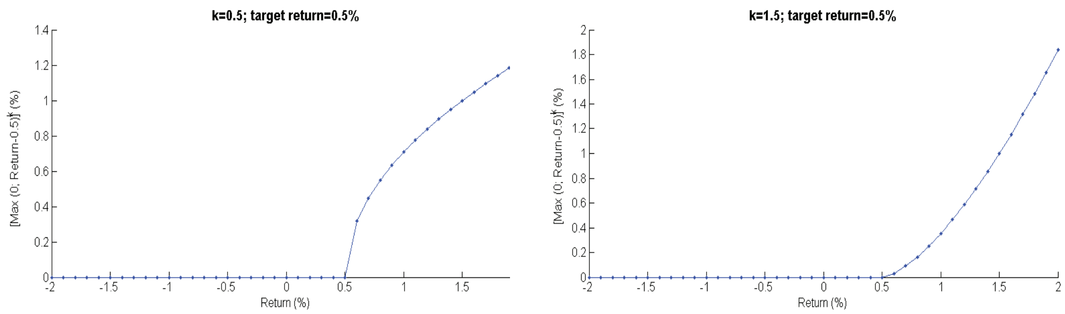

Figure 3.3
Variations of (p-q) in the Farinelli-Tibiletti ratio - 2003

Figure 3.4
Variations of (p-q) in the Farinelli-Tibiletti ratio - 2004

Figure 3.5
Variations of (p-q) in the Farinelli-Tibiletti ratio - 2005

Figure 3.6
Variations of (p-q) in the Farinelli-Tibiletti ratio - 2006

Table 3.1
Alternative performance measures

Alternative performance measures	Attitude towards gains	Attitude towards losses
$Omega\,ratio(r_i) = \frac{(UPM_1(r_i))}{(LPM_1(r_i))}$	Small gains and large gains are weighted equally	Small losses and large losses are weighted equally
	Always positive and Downside risk	
$Upside\,potential\,ratio(r_i) = \frac{(UPM_1(r_i))}{\sqrt{(LPM_2(r_i))}}$	Small gains and large gains are weighted equally	Large losses are undesired
	Integration of loss aversion	
$Farinelli - Tibiletti_{(0.5-2)}\ ratio(r_i) = \frac{(UPM_{0.5}(r_i))^{1/0.5}}{\sqrt{(LPM_2(r_i))}}$	Small gains are favored over large but low probable gains	Large losses are undesired
	Consideration of the Expected utility function	
$Farinelli - Tibiletti_{(0.8-0.85)}\ ratio(r_i) = \frac{(UPM_{0.8}(r_i))^{1/0.85}}{(LPM_{0.8}(r_i))^{1/0.85}}$	Small gains are favored over large but low probable gains	Losses are undesired, no matter their magnitude
	Consideration of the S-Shaped Value function	
$Farinelli - Tibiletti_{(1.5-2)}\ ratio(r_i) = \frac{(UPM_{1.5}(r_i))^{1/1.5}}{\sqrt{(LPM_2(r_i))}}$	Large but low probable gains are favored	Large losses are undesired
	Consideration of the Behavioral Portfolio Theory	

This table presents the alternative performance measures considered in this paper. Attitude towards gain and losses implied by the parameters values are detailed for each measure.

Table 3.2
Descriptive statistics

	2003	2004	2005	2006
Panel A : Investors				
Number of investors	24,766			
Proportion of men	80.4 %			
Panel B : Transactions				
Total number of trades	444,155	431,022	512,309	651,801
Average number of trades per investor	17.9 (2)	17.4 (2)	20.7 (4)	26.3 (5)
Purchase monthly turnover (%)	7.2 (1.3)	5.9 (1.1)	6.4 (1.2)	7.8 (1.7)
Sale monthly turnover (%)	7.2 (1.5)	6.2 (1.6)	7.1 (2.2)	8.7 (2.9)
Panel C: Portfolios				
Portfolio value (Euros)	24,241 (9455)	27,901 (10,935)	31,259 (11,293)	36,629 (13,252)
Number of different stocks in portfolio	8.6 (6.3)	8.4 (6.2)	8 (6)	7.8 (5.5)
Annual return (%)	31.40 (27.53)	8.16 (8.47)	28.03 (26.94)	22.05 (20.27)
Annual Jensen α (%)	6.99 (5.71)	-3.83 (-2.95)	2.54 (3.04)	-2.38 (-2.44)
Annual Skewness	0.76 (0.74)	-0.09 (-0.16)	-0.06 (-0.16)	-0.38 (-0.50)

This table presents statistics on the dataset during the period 2003 to 2006. Panel A is related to investors. Panel B provides yearly information on transactions, averaged across investors. The monthly turnover is computed as the market value of shares purchased or sold in month t, divided by the mean market value of all shares held in the portfolio during month t. Panel C reports yearly information on investor portfolios, averaged across investors. The portfolio value and the number of stocks are calculated in the mi-year. Annual returns and skewness are computed based on weekly returns. Medians are reported in parentheses.

Table 3.3
Rank correlations with the Sharpe ratio

	2003	*2004*	*2005*	*2006*
	Spearman correlations (%)			
Omega ratio	97.92	98,.44	97.90	98.79
Upside Potential ratio	91.81	94.88	91.71	89.59
Farinelli-Tibiletti(0.5-2) ratio	70.74	71.11	85.11	79.72
Farinelli-Tibiletti(0.8-0.85) ratio	66.11	64.38	82.77	76.70
Farinelli-Tibiletti(1.5-2) ratio	33.72	30.59	41.58	42.26
	Kendall correlations (%)			
Omega ratio	93.22	94.74	93.52	96.06
Upside Potential ratio	81.71	86.35	81.18	77.71
Farinelli-Tibiletti(0.5-2) ratio	57.42	57.04	71.70	65.61
Farinelli-Tibiletti(0.8-0.85) ratio	52.79	51.26	69.74	62.78
Farinelli-Tibiletti(1.5-2) ratio	25.86	23.17	30.94	32.60

This table presents the relationship between the rankings of investors resulting from the evaluation of investor's performance with alternative measures and the Sharpe ratio. The Spearman ρ and the Kendall τ are computed each year between 2003 and 2006.

Table 3.4
Transition matrices - Sharpe ratio/Omega ratio

					Sharpe/Omega - 2003					
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	100,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
2	55,9	43,9	0,2	0,0	0,0	0,0	0,0	0,0	0,0	0,0
3	0,0	49,8	49,3	0,8	0,0	0,0	0,0	0,0	0,0	0,0
4	0,0	0,0	43,8	52,8	2,9	0,4	0,0	0,0	0,0	0,0
5	0,0	0,0	0,5	39,6	52,6	6,4	0,5	0,2	0,1	0,1
6	0,0	0,0	0,0	0,6	37,7	52,7	8,0	0,6	0,3	0,1
7	0,0	0,0	0,0	0,0	0,6	33,6	56,0	9,2	0,4	0,2
8	0,0	0,0	0,0	0,0	0,0	0,6	28,9	56,7	13,2	0,6
9	0,0	0,0	0,0	0,0	0,0	0,0	0,4	27,1	61,9	10,6
10	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	17,9	82,1
					Sharpe/Omega - 2004					
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	40,4	40,4	19,1	0,0	0,0	0,0	0,0	0,0	0,0	0,0
2	0,0	0,0	63,0	37,0	0,0	0,0	0,0	0,0	0,0	0,0
3	0,0	0,0	0,0	79,8	20,1	0,0	0,0	0,0	0,0	0,0
4	0,0	0,0	0,0	0,3	95,2	4,5	0,0	0,0	0,0	0,0
5	0,0	0,0	0,0	0,0	6,6	91,4	2,0	0,0	0,0	0,0
6	0,0	0,0	0,0	0,0	0,0	23,8	74,7	1,4	0,0	0,0
7	0,0	0,0	0,0	0,0	0,0	0,0	42,8	56,5	0,6	0,0
8	0,0	0,0	0,0	0,0	0,0	0,0	0,0	61,6	38,2	0,2
9	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	79,7	20,3
10	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	1,0	99,0
					Sharpe/Omega - 2005					
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	100,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
2	29,8	69,5	0,7	0,0	0,0	0,0	0,0	0,0	0,0	0,0
3	0,0	27,1	70,9	1,8	0,1	0,1	0,0	0,0	0,0	0,0
4	0,0	0,0	25,1	69,0	5,0	0,4	0,2	0,1	0,1	0,0
5	0,0	0,0	0,0	26,0	65,8	6,2	1,1	0,4	0,2	0,4
6	0,0	0,0	0,0	0,0	25,8	63,6	8,5	1,4	0,4	0,4
7	0,0	0,0	0,0	0,0	0,0	26,4	55,2	16,8	1,3	0,4
8	0,0	0,0	0,0	0,0	0,0	0,1	30,8	54,4	13,2	1,6
9	0,0	0,0	0,0	0,0	0,0	0,0	0,2	24,4	64,8	10,7
10	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	16,7	83,3
					Sharpe/Omega - 2006					
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	100,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
2	3,7	94,6	1,7	0,0	0,0	0,0	0,0	0,0	0,0	0,0
3	0,0	4,9	89,9	5,1	0,1	0,0	0,0	0,0	0,0	0,0
4	0,0	0,0	8,0	83,8	7,9	0,2	0,0	0,0	0,0	0,0
5	0,0	0,0	0,0	10,7	78,1	10,3	0,8	0,1	0,0	0,1
6	0,0	0,0	0,0	0,0	13,6	73,7	10,9	1,5	0,2	0,2
7	0,0	0,0	0,0	0,0	0,0	15,4	71,7	11,7	0,8	0,4
8	0,0	0,0	0,0	0,0	0,0	0,0	16,2	72,0	10,8	1,0
9	0,0	0,0	0,0	0,0	0,0	0,0	0,0	14,4	75,6	10,1
10	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	12,2	87,8

This table presents the transition matrices between the ranking resulting from the Sharpe ratio evaluation and the Omega ratio evaluation for 2003, 2004, 2005 and 2006. We report the conditional probability to be ranked in decile j with the Omega ratio (in columns) given that the investor is ranked in decile i according to the Sharpe ratio (in rows).

Table 3.5
Transition matrices - Sharpe ratio/Upside Potential ratio

					Sharpe/UPR - 2003					
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	97,9	2,0	0,1	0,0	0,0	0,0	0,0	0,0	0,0	0,0
2	47,3	39,0	10,4	2,5	0,5	0,3	0,0	0,0	0,0	0,0
3	8,0	36,2	32,1	15,9	5,3	1,7	0,6	0,3	0,0	0,0
4	1,0	12,1	32,3	28,9	16,0	6,6	2,0	0,8	0,2	0,0
5	0,3	3,6	12,8	26,8	30,3	17,5	6,2	1,8	0,5	0,2
6	0,0	1,2	4,2	13,3	26,3	30,2	17,8	5,8	1,2	0,1
7	0,1	0,6	1,3	4,2	11,6	25,3	32,5	19,4	4,5	0,6
8	0,0	0,2	0,5	1,7	3,0	8,9	26,1	36,1	21,5	2,0
9	0,0	0,1	0,2	0,4	0,8	3,0	7,6	25,3	46,6	16,0
10	0,0	0,0	0,0	0,0	0,1	0,5	1,1	4,3	19,1	74,9
					Sharpe/UPR - 2004					
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	39,4	34,4	21,2	4,4	0,4	0,1	0,0	0,0	0,0	0,0
2	2,3	12,5	34,2	38,9	11,1	1,1	0,0	0,0	0,0	0,0
3	0,3	3,5	14,6	36,6	31,1	13,5	0,4	0,0	0,0	0,0
4	0,2	1,0	5,5	19,3	42,6	26,1	5,0	0,4	0,0	0,0
5	0,1	0,6	1,8	8,4	23,3	39,6	23,4	2,4	0,4	0,0
6	0,0	0,1	0,5	2,3	8,9	27,8	42,1	16,6	1,7	0,0
7	0,0	0,0	0,0	0,6	1,5	10,0	34,6	42,8	10,1	0,1
8	0,0	0,0	0,0	0,0	0,3	1,1	11,4	42,8	41,8	2,5
9	0,0	0,0	0,0	0,0	0,0	0,4	2,6	14,1	57,6	25,3
10	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,4	7,9	91,6
					Sharpe/UPR - 2005					
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	97,4	2,6	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
2	29,9	58,3	10,7	0,8	0,0	0,2	0,0	0,0	0,0	0,0
3	1,5	32,5	44,0	17,4	3,6	0,9	0,1	0,0	0,0	0,0
4	0,0	4,0	32,6	36,0	17,3	6,8	2,2	0,7	0,3	0,1
5	0,0	0,2	8,7	28,7	29,5	19,1	8,1	3,6	1,0	1,0
6	0,0	0,0	0,7	11,8	28,0	25,2	18,1	11,3	3,6	1,3
7	0,0	0,0	0,0	1,8	13,9	24,4	23,1	16,8	17,5	2,5
8	0,0	0,0	0,0	0,1	3,4	17,0	25,5	23,1	18,7	12,2
9	0,0	0,0	0,0	0,0	0,2	3,9	17,8	28,2	26,8	23,2
10	0,0	0,0	0,0	0,0	0,0	0,0	1,8	13,0	28,8	56,4
					Sharpe/UPR - 2006					
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	72,8	20,7	5,7	0,8	0,1	0,0	0,0	0,0	0,0	0,0
2	22,1	40,1	19,2	15,9	2,0	0,4	0,1	0,3	0,0	0,0
3	6,3	26,7	32,3	20,3	9,1	3,5	1,5	0,3	0,0	0,0
4	1,2	9,4	25,1	25,7	20,8	11,9	4,5	1,1	0,4	0,0
5	0,1	2,9	11,2	20,8	24,7	17,9	15,2	5,6	1,3	0,2
6	0,0	0,6	4,9	10,5	22,1	26,4	15,3	12,3	6,8	1,0
7	0,0	0,0	1,3	4,2	13,6	21,5	29,5	18,6	8,8	2,5
8	0,0	0,0	0,3	1,4	6,2	13,2	23,1	29,5	20,0	6,3
9	0,0	0,0	0,0	0,1	1,0	4,4	9,4	26,8	37,8	20,5
10	0,0	0,0	0,0	0,0	0,1	0,4	0,9	5,2	24,4	69,0

This table presents the transition matrices between the ranking resulting from the Sharpe ratio evaluation and the Upside Potential ratio evaluation for 2003, 2004, 2005 and 2006. We report the conditional probability to be ranked in decile j with the Upside Potential ratio (in columns) given that the investor is ranked in decile i according to the Sharpe ratio (in rows).

Table 3.6
Transition matrices - Sharpe ratio/Farinelli-Tibiletti(0.5-2) ratio

	1	2	3	4	5	6	7	8	9	10
					Sharpe/Farinelli-Tibiletti(0.5-2) - 2003					
1	83,2	12,4	2,9	0,8	0,4	0,2	0,1	0,0	0,0	0,0
2	30,4	32,8	18,0	7,7	4,8	3,6	0,9	0,6	0,3	0,8
3	12,1	22,5	21,7	17,7	11,4	6,7	4,2	2,5	1,0	0,3
4	6,6	10,5	17,1	19,9	15,2	12,0	11,3	4,2	2,3	0,8
5	3,1	7,5	12,8	15,4	16,4	15,9	13,9	10,1	4,2	0,9
6	5,5	5,8	8,0	11,3	14,1	16,4	17,0	13,0	6,8	2,2
7	1,6	4,2	5,8	8,5	11,7	15,5	16,9	17,7	13,3	4,9
8	1,9	2,8	4,3	6,5	10,5	12,2	14,0	19,5	20,8	7,6
9	0,5	2,0	3,2	3,9	5,8	6,9	10,0	17,1	26,6	24,0
10	0,6	1,1	2,0	2,7	3,7	4,5	5,6	9,1	18,4	52,3
					Sharpe/Farinelli-Tibiletti(0.5-2) - 2004					
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	34,1	23,8	15,4	10,1	7,1	4,3	2,6	1,5	1,1	0,0
2	8,5	15,8	17,5	17,8	14,9	11,0	8,7	3,3	2,3	0,3
3	3,8	10,5	12,9	15,2	14,6	13,1	11,8	8,2	8,9	1,0
4	3,8	8,3	13,0	13,2	14,1	12,5	12,4	16,8	5,0	0,9
5	1,5	6,3	10,9	14,5	13,2	14,7	13,9	13,2	9,2	2,7
6	0,5	4,2	7,5	10,1	14,7	15,7	16,1	12,5	12,5	6,2
7	0,2	1,4	4,9	10,3	12,7	15,5	15,6	15,5	14,2	9,7
8	0,2	1,0	2,0	5,2	9,6	14,7	16,7	19,5	19,4	11,8
9	0,2	1,5	5,3	2,8	4,5	8,1	13,4	18,7	24,1	21,4
10	0,0	0,0	0,1	0,6	0,4	1,7	3,4	7,8	20,6	65,4
					Sharpe/Farinelli-Tibiletti(0.5-2) - 2005					
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	72,2	23,0	4,4	0,3	0,0	0,0	0,1	0,0	0,0	0,0
2	35,7	30,3	18,9	10,2	2,6	1,6	0,4	0,2	0,1	0,0
3	10,4	29,5	27,6	16,6	9,1	3,6	1,4	0,9	0,5	0,3
4	2,2	16,1	23,7	21,4	15,3	9,1	5,9	4,0	1,7	0,5
5	0,1	4,3	15,1	24,4	20,5	13,8	9,8	6,8	3,0	2,0
6	0,0	1,0	6,9	15,6	23,2	19,7	14,3	10,1	5,6	3,7
7	0,0	0,0	1,3	6,5	16,8	21,6	23,0	13,1	10,2	7,5
8	0,0	0,0	0,3	1,5	7,6	17,2	22,0	21,4	15,3	14,7
9	0,0	0,0	0,0	0,2	1,5	7,2	17,9	26,1	30,2	17,0
10	0,0	0,0	0,0	0,0	0,0	0,9	3,9	14,1	30,1	51,0
					Sharpe/Farinelli-Tibiletti(0.5-2) - 2006					
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	66,7	20,3	8,1	3,9	0,7	0,3	0,0	0,1	0,0	0,0
2	18,9	28,0	19,1	16,2	6,2	9,9	1,1	0,4	0,2	0,0
3	10,4	24,3	24,6	14,7	10,1	7,3	4,5	2,6	1,4	0,1
4	4,2	13,3	20,1	19,9	14,9	9,4	7,5	6,6	3,3	0,7
5	1,0	9,7	14,6	18,2	19,2	14,1	9,5	7,9	4,2	1,6
6	0,6	2,9	7,8	13,2	19,6	16,8	14,6	11,1	8,0	5,5
7	0,2	1,0	3,5	8,0	13,3	19,3	24,7	13,8	10,3	5,8
8	0,2	0,7	1,5	4,0	10,9	13,9	19,5	21,9	17,1	10,3
9	0,1	0,1	0,6	1,3	4,1	7,2	14,0	24,6	26,0	21,9
10	0,0	0,1	0,1	0,5	0,6	1,4	4,1	10,7	29,0	53,6

This table presents the transition matrices between the ranking resulting from the Sharpe ratio evaluation and the Farinelli-Tibiletti(0.5-2) ratio evaluation for 2003, 2004, 2005 and 2006. We report the conditional probability to be ranked in decile j with the Farinelli-Tibiletti(0.5-2) ratio (in columns) given that the investor is ranked in decile i according to the Sharpe ratio (in rows).

Table 3.7
Transition matrices - Sharpe ratio/Farinelli-Tibiletti(0.8-0.85) ratio

	Sharpe/Farinelli-Tibiletti(0.8-0.85) - 2003									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	50,3	22,6	13,2	8,8	3,6	1,4	0,0	0,1	0,0	0,0
2	30,2	21,7	16,3	11,7	7,2	6,0	3,4	1,7	1,5	0,2
3	16,9	21,1	17,9	13,9	12,1	7,5	4,3	4,2	1,9	0,2
4	8,9	13,8	15,9	18,0	13,4	10,5	8,2	7,6	3,0	0,8
5	4,9	9,3	12,3	16,2	16,5	15,1	12,7	7,7	3,9	1,4
6	6,8	6,7	9,2	10,9	15,6	16,4	16,3	9,7	6,1	2,2
7	2,5	5,2	6,7	7,6	11,4	16,8	18,1	16,6	10,5	4,7
8	2,5	3,2	5,3	5,9	7,5	9,7	15,5	20,5	22,6	7,3
9	1,3	2,7	3,2	3,8	4,8	6,6	9,6	16,8	26,9	24,4
10	0,9	1,6	1,9	2,6	3,8	4,7	5,6	9,0	17,4	52,6
	Sharpe/Farinelli-Tibiletti(0.8-0.85) - 2004									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	34,3	20,1	12,9	9,5	7,1	4,9	4,2	3,0	2,2	1,7
2	8,9	19,1	17,0	14,3	10,7	9,8	7,2	6,9	4,4	1,7
3	4,7	13,3	14,2	13,0	11,1	10,6	8,9	7,2	14,8	2,3
4	2,7	12,1	15,2	13,1	13,1	10,2	14,6	8,8	7,3	3,0
5	1,3	8,5	14,2	15,4	13,0	13,2	11,9	9,7	8,1	4,7
6	0,4	4,7	10,0	14,0	15,5	15,0	13,0	10,9	8,9	7,4
7	0,1	1,9	7,2	12,3	15,7	15,4	14,1	13,0	13,3	6,9
8	0,0	0,4	3,1	7,0	13,0	16,8	16,5	20,3	13,3	9,5
9	0,0	0,0	0,4	2,4	6,1	12,6	17,0	23,1	19,3	19,0
10	0,0	0,0	0,0	0,0	0,4	1,5	4,1	10,8	23,3	59,9
	Sharpe/Farinelli-Tibiletti(0.8-0.85) - 2005									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	73,1	22,1	3,4	1,0	0,3	0,1	0,0	0,1	0,0	0,0
2	37,2	29,6	14,2	8,5	4,3	2,0	1,6	1,2	1,0	0,3
3	9,5	31,5	27,0	12,7	7,6	4,6	3,2	2,0	1,0	0,8
4	1,1	17,2	27,2	20,8	11,8	7,7	6,5	3,6	2,2	2,0
5	0,0	3,2	19,1	26,6	18,2	11,6	7,3	6,6	4,1	3,4
6	0,0	0,4	5,9	20,0	25,7	18,2	10,8	8,2	5,7	4,9
7	0,0	0,0	0,7	6,5	19,4	23,7	21,8	10,7	8,9	8,2
8	0,0	0,0	0,1	1,1	8,3	21,0	22,6	19,3	13,4	14,3
9	0,0	0,0	0,0	0,2	1,1	7,3	19,6	29,0	28,2	14,7
10	0,0	0,0	0,0	0,0	0,1	0,4	3,2	16,1	32,1	48,1
	Sharpe/Farinelli-Tibiletti(0.8-0.85) - 2006									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	63,7	17,7	6,6	4,9	2,9	1,7	1,2	1,1	0,3	0,0
2	20,6	25,5	21,6	9,8	14,0	3,1	2,0	1,6	1,2	0,7
3	11,0	29,2	19,9	13,1	7,0	7,2	4,8	4,1	2,9	0,9
4	4,5	14,5	23,2	18,9	11,0	8,6	7,0	6,4	4,4	1,5
5	1,2	9,3	16,7	21,1	16,5	11,4	8,8	6,8	5,8	2,5
6	0,8	2,6	7,3	18,0	18,5	16,9	12,0	10,4	7,3	6,3
7	0,2	1,0	3,1	8,7	15,7	21,8	20,9	11,7	9,8	6,9
8	0,2	0,6	1,1	4,3	10,8	18,5	20,6	18,3	14,4	11,1
9	0,0	0,0	0,4	0,8	2,8	9,2	18,5	25,7	22,8	19,7
10	0,0	0,0	0,0	0,1	0,4	1,4	3,8	13,5	30,4	50,3

This table presents the transition matrices between the ranking resulting from the Sharpe ratio evaluation and the Farinelli-Tibiletti(0.8-0.85) ratio evaluation for 2003, 2004, 2005 and 2006. We report the conditional probability to be ranked in decile j with the Farinelli-Tibiletti(0.8-0.85) ratio (in columns) given that the investor is ranked in decile i according to the Sharpe ratio (in rows).

Table 3.8
Transition matrices - Sharpe ratio/Farinelli-Tibiletti(1.5-2) ratio

					Sharpe/Farinelli-Tibiletti(1.5-2) - 2003					
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	16,4	9,6	9,1	7,3	6,7	8,8	9,0	12,3	11,1	9,7
2	16,5	15,2	12,1	11,2	10,0	8,5	8,8	7,8	6,1	3,9
3	13,9	16,3	15,5	12,9	11,0	9,3	7,1	6,6	4,8	2,6
4	10,6	13,3	15,3	13,1	11,3	9,9	8,9	8,7	4,9	3,9
5	8,8	11,5	13,4	13,6	12,6	13,1	9,8	8,0	5,1	4,1
6	11,3	9,7	10,6	13,4	12,6	13,5	10,6	7,9	6,5	3,9
7	7,1	7,5	8,3	11,0	14,1	12,6	13,0	11,0	9,7	5,7
8	6,8	6,4	6,9	7,0	9,7	11,8	12,2	14,1	13,9	11,0
9	5,5	5,7	3,9	5,3	5,8	7,4	12,2	15,2	21,7	17,3
10	7,2	4,5	4,2	3,4	4,1	4,4	7,8	9,8	16,8	37,8
					Sharpe/Farinelli-Tibiletti(1.5-2) - 2004					
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	23,9	13,8	10,9	8,6	7,8	7,8	7,2	7,8	6,7	5,5
2	12,9	14,1	11,6	8,9	8,6	8,7	8,9	10,2	8,7	7,3
3	8,8	12,2	10,4	10,0	7,7	7,5	9,4	8,5	9,3	16,2
4	8,8	11,4	10,8	11,1	9,1	9,0	14,2	8,0	8,6	9,1
5	7,0	10,9	13,2	11,4	11,7	10,2	9,2	10,1	8,4	7,9
6	5,2	10,5	12,0	11,1	10,6	12,1	9,6	10,5	10,0	8,4
7	3,3	8,1	11,1	13,5	11,6	12,4	10,7	9,4	12,5	7,4
8	2,0	6,5	9,5	11,9	13,0	14,0	12,5	14,1	9,8	6,7
9	0,9	4,2	7,3	11,8	16,6	12,2	12,1	11,5	12,3	11,1
10	0,0	0,6	1,5	4,5	7,7	10,4	11,8	14,3	20,1	29,0
					Sharpe/Farinelli-Tibiletti(1.5-2) - 2005					
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	37,0	20,7	9,7	9,2	15,1	2,3	2,0	1,7	1,4	0,9
2	26,7	15,0	11,6	10,2	7,2	6,3	6,6	4,8	4,8	6,8
3	16,9	17,1	11,5	9,8	7,4	9,8	7,5	7,3	6,6	6,2
4	12,0	12,0	12,7	11,3	10,0	8,5	9,1	8,5	8,6	7,3
5	7,7	12,5	12,8	10,1	10,4	9,4	9,8	8,6	9,4	9,3
6	4,6	10,3	12,5	9,5	10,5	11,3	11,6	11,1	9,1	9,5
7	2,1	8,0	9,4	11,2	9,9	10,4	10,4	11,3	16,0	11,2
8	1,4	4,9	9,6	11,0	10,5	12,6	11,1	11,2	12,8	15,0
9	0,3	2,5	7,3	11,0	11,8	12,1	12,5	15,5	12,4	14,7
10	0,1	0,5	2,9	6,5	9,0	14,8	16,8	17,4	16,1	15,9
					Sharpe/Farinelli-Tibiletti(1.5-2) - 2006					
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	40,6	11,8	8,8	8,0	5,4	5,8	6,0	5,4	4,3	4,0
2	17,1	13,4	15,6	7,8	6,6	5,4	8,2	7,3	11,7	6,6
3	17,3	18,1	11,3	10,3	8,5	7,4	6,9	7,8	6,1	6,2
4	10,4	16,7	12,5	12,1	10,9	10,5	7,7	6,9	7,2	5,0
5	6,7	12,9	13,7	13,0	14,6	10,9	9,7	6,1	7,7	4,9
6	4,3	10,5	12,1	14,0	12,1	11,5	11,3	7,2	8,6	8,4
7	1,9	8,0	10,4	11,8	13,0	12,0	13,5	14,5	8,1	6,8
8	1,7	5,6	9,1	12,1	13,3	14,2	12,0	12,7	10,4	9,1
9	0,9	2,4	4,9	7,8	10,8	14,1	13,6	15,3	15,8	14,4
10	0,4	0,8	1,6	3,0	4,7	8,0	10,7	14,9	21,5	34,3

This table presents the transition matrices between the ranking resulting from the Sharpe ratio evaluation and the Farinelli-Tibiletti(1.5-2) ratio evaluation for 2003, 2004, 2005 and 2006. We report the conditional probability to be ranked in decile j with the Farinelli-Tibiletti(1.5-2) ratio (in columns) given that the investor is ranked in decile i according to the Sharpe ratio (in rows).

Table 3.9
Impact of the choice of alternative measures

	Max. down-grade	Max. up-grade	No change (%)	Down-graded (%)	Up-graded (%)
			2003		
Omega ratio	-5	2	58.20	5.85	35.94
Upside Potential ratio	-6	8	41.34	19.07	39.59
Farinelli-Tibiletti(0.5-2) ratio	-8	9	27.09	32.50	40.41
Farinelli-Tibiletti(0.8-0.85) ratio	-8	9	24.28	33.65	42.07
Farinelli-Tibiletti(1.5-2) ratio	-9	9	17.35	36.19	46.45
			2004		
Omega ratio	-3	1	36.25	63.67	0.08
Upside Potential ratio	-5	6	36.84	55.96	7.20
Farinelli-Tibiletti(0.5-2) ratio	-9	8	24.78	50.04	25.19
Farinelli-Tibiletti(0.8-0.85) ratio	-9	7	24.22	46.35	29.43
Farinelli-Tibiletti(1.5-2) ratio	-9	9	16.40	47.33	36.27
			2005		
Omega ratio	-6	2	68.61	7.36	24.03
Upside Potential ratio	-6	4	40.07	22.84	37.09
Farinelli-Tibiletti(0.5-2) ratio	-8	5	30.36	27.76	41.88
Farinelli-Tibiletti(0.8-0.85) ratio	-8	5	28.97	25.83	45.20
Farinelli-Tibiletti(1.5-2) ratio	-9	9	13.87	38.85	47.28
			2006		
Omega ratio	-5	1	82.64	7.41	9.95
Upside Potential ratio	-6	5	38.65	29.09	32.26
Farinelli-Tibiletti(0.5-2) ratio	-8	8	29.99	32.54	37.47
Farinelli-Tibiletti(0.8-0.85) ratio	-8	7	27.21	31.38	41.41
Farinelli-Tibiletti(1.5-2) ratio	-9	9	17.90	36.74	45.35

This table contains the change in decile of investors when their performance is evaluated with alternative measures rather than with the Sharpe ratio. The maximum downgrade and upgrade are presented as well as the proportion of investors who remain in the same decile, and those who are downgraded and upgraded.

Table 3.10
Decile of the market index performance

	2003	**2004**	**2005**	**2006**
Sharpe ratio	6	9	9	9
Omega ratio	6	9	9	9
Upside Potential ratio	4	7	9	10
Farinelli-Tibiletti(0.5-2) ratio	3	7	8	6
Farinelli-Tibiletti(0.8-0.85) ratio	3	6	7	5
Farinelli-Tibiletti(1.5-2) ratio	1	1	4	5

This table reports the decile of the market index each year between 2003 and 2006, according to 6 performance measures. These grades are based on the initial ranking computed each year for each measure across 24,766 investors.

Table 3.11
Performance persistence

	1 year	%	**2 years**	%	**3 years**	%	**4 years**	%
Sharpe ratio	10564	42.66	1157	4.67	277	1.12	66	0.27
Omega ratio	9906	40.00	1249	5.04	254	1.03	56	0.23
Upside Potential ratio	14860	60.00	4469	18.04	609	2.46	0	0.00
Farinelli-Tibiletti(0.5-2) ratio	17336	70.00	5436	21.95	1136	4.59	640	2.58
Farinelli-Tibiletti(0.8-0.85) ratio	17336	70.00	7204	29.09	2118	8.55	1471	5.94
Farinelli-Tibiletti(1.5-2) ratio	22289	90.00	20151	81.37	11927	48.16	7549	30.48

This table reports the number and the proportion of investors who are ranked in a higher decile than the market index with each alternative performance measure. The first row indicates the number of the consecutive year (1, 2, 3 or 4 starting from 2003) during which investors beat the market.

Table 3.12
Market index decile among hazard portfolios

	2003	2004	2004	2006
Sharpe ratio	4	9	10	7
Omega ratio	3	9	10	9
Upside Potential ratio	2	7	9	9
Farinelli-Tibiletti(0.5-2) ratio	1	1	1	1
Farinelli-Tibiletti(0.8-0.85) ratio	1	1	1	1
Farinelli-Tibiletti(1.5-2) ratio	1	1	1	1

This table reports the decile of the performance of the market index each year between 2003 and 2006, according to 6 performance measures. These grades are based on the ranking of 24,677 randomly created portfolios that mimic the diversification level of investors in our sample.

Chapter 4

Repurchase behavior of individual investors, sophistication and regret

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Abstract

Based on a sample of more than 6 million trades from a large brokerage house, we investigate the stock repurchase behavior of individual investors from 1999 to 2006. Using survival analysis techniques we show that investors prefer to repurchase stocks that they previously sold for a gain and stocks that have lost value since being sold. With direct measures of sophistication including diversification, foreign investments and several brokerage accounts, we find that less sophisticated investors are more prone to such repurchase behavior. Our findings emphasize the importance of individual attributes on the impact of anticipated and experienced regret on financial decisions.

4.1 Introduction

According to standard finance models, investment decisions should be based on thoughtful expectations of future stock prices. Consequently, purchase or repurchase decisions should be independent of past stock performances, of the memory associated with their sale, and of behavioral biases. However, when rebalancing their portfolios, investors are prone to simplify the decision-making process by reducing the set of possibilities they face. Concerning purchase behavior, investors tend to buy stocks that grab their attention, e.g., stocks in the news, stocks experiencing abnormal volumes or stocks with extreme performances (Barber and Odean, 2008). This attention-based buying behavior is confirmed for other attention-grabbing events, such as stocks hitting upper price limits (Seasholes and Wu, 2007), dividend announcements (Graham and Kumar, 2006) and earnings announcements (Lee, 1992). Moreover, investors are more likely to invest in familiar stocks while ignoring the principles of diversification (Huberman, 2001; Grinblatt and Keloharju, 2001). Given the extrapolation bias, they tend to prefer past winning stocks (De Bondt, 1998; Barber, Odean, and Zhu, 2009b).

More recently, Strahilevitz, Odean, and Barber (2011) established two patterns of repurchase selection for a U.S. database of 78,000 households from January 1991 through December 1996. They found that, on an aggregate level, investors prefer to (1) repurchase stocks they previously sold for a gain and (2) repurchase stocks that have lost value since being sold.[1] Strahilevitz, Odean, and Barber (2011) explain their

[1] Regarding the first pattern, Nofsinger and Varma (2013) find that the recency of stock sales plays a profound role in repurchasing behavior, which dominates the impact of prior profitability. The authors show that the repurchasing decision for a stock appears to be mostly dependent on the

results by focusing on the role of emotions, showing that such behavior is primarily motivated by an investors desire to avoid regret. An investor whose sale results in a loss experiences regret from purchasing the stock because its performance failed to meet her expectations. To diminish this feeling, she tends to avoid this stock in future trades. Indeed, a repurchase would prolong the regret. If the stock price has increased since the previous sale, the investor knows that she could have obtained a better outcome by selling later. She anticipates that repurchasing the stock will intensify that regret; therefore, she prefers to ignore this stock. In contrast, investors attempt to engage in trades that yield positive emotions, such as pride. As a result, they are more prone to repurchase stocks whose sales resulted in a profit.

In contrast to previous work, our main objective is to study repurchase behavior at the individual level. Our approach enables us to measure how individual attributes, such as sophistication, impact repurchase behavior. More generally, we investigate the ability of sophisticated investors to reduce the effect of psychological factors on their financial decisions.

Sophistication corresponds to the level of knowledge on financial markets and expertise in financial instruments. Numerous studies report that investor sophistication helps to decrease some biases such as the disposition effect, i.e., the tendency to more readily sell winners than losers (Calvet, Campbell, and Sodini, 2009; Dhar and Zhu, 2006; Grinblatt, Keloharju, and Linnainmaa, 2011). Along the same lines, sophisti-

timing of trades of other stocks. Actually, the recency of another stocks sale decreases the propensity to repurchase a given stock by 23%.

cated investors have a lesser tendency to invest in their company's stocks (Agnew, 2006; Kimball and Shumway, 2010) and are less prone to underdiversify (Calvet, Campbell, and Sodini, 2009; Goetzmann and Kumar, 2008).[2] However, when sophisticated investors are endowed with informational advantages, they might choose to hold more concentrated portfolios and to favor local stocks, resulting in higher performance (Korniotis and Kumar, 2013).

The repurchase behaviors are not much explored in the literature. We examine whether financial expertise increases the propensity of repurchases backed by objective incentives. To identify sophisticated investors, researchers often rely on socio-demographic variables such as income, education level, age, place of living or family size (Calvet, Campbell, and Sodini, 2009; Dhar and Zhu, 2006). These estimators are indirect, i.e., they imply assumptions regarding the access to information, the processing of information and the financial education of wealthier, older, more educated and urbain investors. Age, place of living and education are correlated to intelligence (Cagney and Lauderdale, 2002; Holtzman, Rebok, Saczynski, Kouzis, Doyle, and Eaton, 2004; Christelis, Jappelli, and Padula, 2010), which is also employed to select sophisticated investors (Grinblatt, Keloharju, and Linnainmaa, 2011; Korniotis and Kumar, 2013; Christelis, Jappelli, and Padula, 2010). Intelligence is evaluated with cognitive capacities (for instance ability to perform numerical operations, planning

[2] The evidence is mixed when considering professional investors, who should be more sophisticated by definition. On the one hand, Kaustia, Alho, and Puttonen (2008) demonstrate that financial market professionals show a much smaller anchoring bias in their long-term stock return expectations than university students. Grinblatt and Keloharju (2000) show that foreign institutional investors are less prone to the home bias. On the other hand Frazzini (2006) shows that U.S. mutual funds exhibit the disposition effect with the same order of magnitude as individual investors.

and executive functions, memory) or with IQ. Another way to measure sophistication lies in direct indicators such as the trading of complex instruments or the tendency to diversify, to invest in foreign stocks, and to short-sell (Korniotis and Kumar, 2013; Feng and Seasholes, 2005; Kimball and Shumway, 2010). These metrics reflect higher skills and a greater understanding of financial markets. Along the same lines, trading experience, measured by the number of trades placed by the investor or the length of time elapsed since account open, constitute dynamic proxies for sophistication. Direct evaluation of sophistication can also be realized through surveys, in which the financial literacy of agents is tested.

In this paper, we offer new evidence relative to the effect of sophistication on investors behavior, showing that sophistication enables investors to weaken the magnitude of their repurchase preferences. Based on the abovementioned works, we proxy for sophistication using foreign stock trading and diversification levels. We add a third measure based on a specific French taxation feature, i.e., the holding of multiple accounts to place trades. Investors trading on the two types of accounts are sophisticated because they take advantage of the flexibility of a traditional account and the tax exoneration of a tax-free account. We show that sophisticated investors, identified through direct measures, are less prone to the repurchase biases documented in this paper, suggesting that sophistications enables investors to be less influenced by their emotions when they trade.
Analyzing more than 6 million trades, this study is the largest to regard the repurchase behavior of individual investors in a European context and offers several

contributions. Our paper differs from previous work because we focus on repurchase behavior at the individual level. This individual analysis considers the existing heterogeneity of behavior. Using survival analysis techniques, we find that sophisticated investors are less prone to have repurchase preferences. Finally, several drivers for such behavior are examined. We show that repurchase patterns are not motivated by private information or investors trading skills. Indeed, they do not earn better returns on their repurchases than on their buys and sales. A contrarian strategy is not able to explain investors preference for repurchasing stocks whose prices have declined since the previous sale. In fact, regarding their purchases, investors are more prone to select stocks whose prices increased during the prior year.

The rest of the paper is organized as follows. We describe the data and sophistication measures in Section 2. The methodology is detailed in Section 3. We present and discuss the results in Section 4. In Section 5, we discuss rational and behavioral drivers for the documented behavior. Section 6 concludes the paper.

4.2 Data and sophistication measures

We start this section with a presentation of the sample, before moving to the description of the sophistication variables.

4.2.1 Data

The main data are provided by a large European brokerage house. We obtain trading records of 84,500 individual investors during the period of 19992006, which consist of 4,232,512 buy trades and 3,839,504 sell trades. The sample contains 2,491 stocks that were traded at least once during the period. The price data come from two sources: Eurofidai[3] for stocks traded on Euronext and Bloomberg for the other stocks. Among the 2,491 stocks, 1,191 are French, and the others come from all over the world but primarily from the U.S. (1,020 stocks). Although American stocks represent a large portion of the dataset, more than 90% of the trades concern French stocks, illustrating the well-known home bias puzzle. The daily portfolio of each investor is computed for the period of January 1999 - December 2006 to compute daily realized returns. To study the repurchase characteristics of investors, we focus on the 34,129 investors who repurchased at least once. We thus drop 51,271 investors who realized 14.7% of the transactions. The descriptive statistics are displayed in table 4.1.

Investors in the final sample trade more than investors in the initial sample. Indeed, in the final sample, the average number of trades is 202, compared with 94 in the initial sample. By construction, the average delay between two consecutive trades is negatively linked to the number of trades. Therefore, the delay is lower in the final sample (38 days) than in the initial sample (52 days). The average number of years for which investors own an active account is higher in the final sample (5.1 years) than in the initial sample (3.7 years). Accounts are considered active when investors realize at least one transaction per year. In the final sample, the average number of shares traded per transaction is 355 for an average trade size of 3,396 Euros. The monthly purchase (sale) turnover is 22.8% (21.2%). The purchase and sale turnover

[3]European financial data institute: https://www.eurofidai.org

can be interpreted as the value of the amount bought and sold in proportion to the monthly portfolio value. Indeed, the monthly turnover is computed as the market value of shares purchased or sold in month t divided by the mean market value of all shares held in the portfolio during month t. Lastly, on average, investors hold 5 different stocks in their portfolio.

4.2.2 Measures of sophistication

In this work, we use 3 variables for considering investors to be more sophisticated than their peers (see table 4.2). First, we follow Feng and Seasholes (2005) and rely on diversification. The literature reports that sophisticated investors are more likely to be conscious of the benefits of diversified investments (Goetzmann and Kumar, 2008; Calvet, Campbell, and Sodini, 2009; Kimball and Shumway, 2010).[4] We start by sorting investors in quintiles according to the average number of stocks in their portfolios over the period 1999-2006. The top diversification quintile corresponds to 10.4 stocks. Our *Diversification* dummy is equal to one if the average number of stocks hold by the investor in his portfolio is at least 10.4 stocks. In other words, we focus on investors sorted in the top quintile.

Second, following the diversification argument and existing results (Kimball and Shumway, 2010; Korniotis and Kumar, 2013), we consider investors who trade foreign stocks to be more sophisticated. As for diversification we sort investors in quintile according to the average number of stocks from different countries in their portfolios.

[4]Other elements are able to explain underdiversification. Liu (2012) shows that underdiversification may be caused by solvency requirement. Korniotis and Kumar (2013) find that underdiversification may be driven by informational advantages.

In the top quintile, investors trade stocks from at least 3 different countries. Our *Foreign Stocks* dummy is equal to one if the investor is sorted in this top quintile. Lastly, the *Two Accounts* dummy is equal to one if the investor holds multiple accounts to place orders: a French PEA and a classic account. A PEA (Plan dEpargne en Action) refers to a tax-free account. These accounts are popular among French investors because capital gains become tax free if an investor holds a PEA account for more than five years. With a PEA, investors are limited to eligible stocks and the usage of the funds of stocks for investment. The eligible stocks are those from any company headquartered in the European Union, Iceland or Norway. At least 75% of the eligible funds must be invested in the eligible stocks. Investors who trade on the two types of accounts are sophisticated because they take advantage of the flexibility of a traditional account and of the tax exoneration of a tax-free account. 47.41% of investors trade on a classic account and French PEA.

Existing literature reports that wealthier investors are sophisticated (Dhar and Zhu, 2006; Calvet, Campbell, and Sodini, 2009; Goetzmann and Kumar, 2008). In accordance with this result, investors who trade on two types of accounts exhibit a higher average wealth (41,654€, with a median of 17,346€) than investors who do not place trades on two types of accounts (27,830€ with a median of 7,711€). As wealth is measured by portfolio value, this check is meaningless for the two diversification variables which imply larger portfolios by definition.

Moreover, Goetzmann and Kumar (2008) and Korniotis and Kumar (2013) find that most sophisticated investors trade options.[5] Our identification of sophisticated investors is consistent with this finding. Investors who are the most diversified, who trade the largest number of foreign stocks and who trade on two types of accounts have a higher propensity to trade warrants. More precisely, 29.2% of investors in the top foreign assets quintile trade warrants, compared to 13.6% for other investors in the ranking. 25.48% of investors in the top diversification quintile trade warrants, compared to 19% for other investors in the ranking. Finally, 23.8% of investors who trade on two types of accounts trade warrants compared to 17.9% for their peers. These relations with other indicators of sophistication reinforce the soundness of our identification.

Table 4.3 contains measures of the associations between the sophistication binary variables. The Pearson Chi-squared test results indicate that sophistication variables are not independent at the 99% confidence level. Column 3 shows the Cramer coefficients, which measure the degree of association between two sets of variables. Although sophistication variables are not independent, Cramers degrees of association are quite low. The highest Cramers coefficient is 29.08% between *Diversification* and *Foreign assets*. We argue that *Diversification* and *Foreign assets* variables do not overlap. An investor can hold a well-diversified portfolio without investing in foreign companies. If the diversification of his portfolio is focused in national stocks, he can be sorted in the top quintile for diversification and in the bottom one for foreign assets at the same time. By contrast, an investor can invest in stocks from 4 different countries, holding only these 4 stocks. In that case, he is sorted in the top quintile for foreign

[5] Other studies show that warrant trading suggests that the investor is seeking entertainment or gambling by trading (Dorn and Sengmueller, 2009).

stocks but not in the top one for diversification.

4.3 Methodology

In this section, we detail our methodology in two distinct parts. In the first part, we describe how we test the existence of the repurchase behavior for the whole sample. The employed methodology is reliable at an aggregate level but is not optimal at the individual level (see Feng and Seasholes (2005) for the same argument on the disposition effect analysis). We address this issue by using survival analysis methods in the second part to examine whether individual attributes decrease repurchase preferences. The survival analysis also constitutes a robustness test for the existence of repurchase behavior.

4.3.1 Repurchase behavior at an aggregate level

To test whether a buy-trade of stock A is a purchase or a repurchase, we must determine the last sale of this asset. Therefore, a delay is needed to analyze past trades (figure 4.1 clarifies this point). We choose to set this period to one year. Given this limit, each sell-trade of stock A that occurred before this year is assumed to no longer be in an investors mind.[6] Now, suppose that the last sale of stock A was realized by the investor in the previous year. To examine repurchase characteristics, one additional year is needed to determine whether purchases are related to this sale. For these reasons and because our database begins on 01-01-1999, we start the analysis

[6]Implicitly, we assume that the investor forgets that she already held this stock in the past, and the buy-trade of stock A is considered a simple purchase and not a repurchase. Results are similar when the delay to analyze past trades is set to 2 years.

of transactions on 01-01-2001.

We first test whether investors are more prone to repurchase stocks previously sold for a gain than stocks previously sold for a loss. According to the efficient market hypothesis, past performance is not a relevant measure for managing a portfolio. Consequently, such a preference is not expected. We follow Strahilevitz, Odean, and Barber (2011) by computing the number of previous winning/losing stocks repurchased divided by the number of opportunities to do so. This method enables us to determine whether the observed repurchase behavior is in fact linked to a previous profit/loss. Actually, a bullish (bearish) market offers more occasions for investors to sell stocks for a gain (a loss). Therefore, simply counting the number of repurchases could bias the results.

To compute the aggregate repurchase rate of prior winners, $PWRR$, and the aggregate repurchase rate of prior losers, $PLRR$, we use the following methodology. For each purchase, we check whether the stock purchased on that day was sold by the same investor during the previous year. Note that one sale is not enough to consider the purchase a repurchase. Indeed, if the stock was already repurchased after the sale, the purchase is an additional purchase and is not taken into account in our study. If the purchase is in fact a repurchase, we determine whether the previous sale constituted a realized gain or a realized loss based on the reference price for the stock. Because the period necessary for studying historical trades is set to one year, the most consistent reference price in our study is the latest price that the investor paid to acquire the security. Next, for each repurchase, we compute the number of winning and losing sales realized by the investor during the previous year. These prior sales represent repurchase opportunities for this investor, including stocks actually repurchased and those that could have been repurchased that day. Lastly, we aggregate winning/losing repurchases and repurchase opportunities of each type over time and across investors as if we consider one representative investor.

$$PWRR = \frac{Number\, of\, prior\, winners\, repurchased}{Number\, of\, opportunities\, to\, repurchase\, prior\, winners} \tag{4.1}$$

$$PLRR = \frac{Number\, of\, prior\, losers\, repurchased}{Number\, of\, opportunities\, to\, repurchase\, prior\, losers} \tag{4.2}$$

At the aggregate level, the null hypothesis is $H0_1 : PWRR - PLRR = 0$.[7]

We then sum all the quantities previously calculated for each investor (number of prior winners/losers repurchased, number of opportunities to repurchase previous winners/losers) to compute individual rates of repurchase $PWRR_i$ and $PLRR_i$.[8]

$$PWRR_i = \frac{\#\, of\, prior\, winners\, repurchased\, by\, investor\, i}{\#\, of\, opportunities\, to\, repurchase\, prior\, winners\, for\, investor\, i} \tag{4.3}$$

---

[7]The t-statistic used to test significance of aggregated results is:

$$t = \frac{(PWRR - PLRR)}{\sigma_{(PWRR-PLRR)}}$$

with

$$\sigma_{(PWRR-PLRR)} = \sqrt{p(1-p)(\frac{1}{W} + \frac{1}{L})}$$

W is the number of opportunities to repurchase previous winners, L is the number of opportunities to repurchase previous winners, p is equal to

$$\frac{(\#\, of\, previous\, winners\, repurchased + \#\, of\, previous\, losers\, repurchased)}{(W + L)}$$

[8]The limitations of these rates computed at the individual level are explained further.

$$PLRR_i = \frac{\#\,of\,prior\,losers\,repurchased\,by\,investor\,i}{\#\,of\,opportunities\,to\,repurchase\,prior\,losers\,for\,investor\,i} \tag{4.4}$$

The individual level analysis enables us to consider the dependence between the successive trades of a particular investor. Indeed, each decision may be correlated to another, such as, for example, when an investor chooses to repurchase the same stock at different dates.

The average $\bar{D}1$ across investors is then computed as $\bar{D}1 = \frac{1}{N}\sum D1_i$ with $D1_i = PWRR_i - PLRR_i$. We calculate this average only for investors who had at least one opportunity to repurchase a stock previously sold for a profit and one opportunity to repurchase a stock previously sold for a loss between 1999 and 2006. At the individual level, the null hypothesis is $H0_2 : \bar{D}1 = 0$.[9]

Next, we test whether investors prefer to repurchase stocks whose price has declined since the previous sale than stocks whose price has increased. With the exception of not checking whether the last sale ends in a gain or a loss, the methodology is the same as the one detailed previously. We observe each purchase and check whether the stock purchased on that day was sold by the same investor during the previous year. We then check if the stock was not already repurchased after the sale. Each day a repurchase is realized, the current price of the stock repurchased is compared with the sale price to determine whether the stock price went up or down since the

[9]The t-statistic used to test the significance of individual results is the following: $t = \frac{\bar{D}1}{\frac{\sigma_{D1}}{\sqrt{n}}}$, with $\sigma_{D1} = \sqrt{\frac{\sum_{i=1}^{n}[D1_i - \bar{D}1]^2}{(n-1)}}$

sale date. The current prices of repurchase opportunities are also gathered to sort between opportunities to repurchase stocks whose prices have increased (declined) since the previous sale.

We count the total number of stocks whose prices have declined/increased since the previous sale and that have been repurchased and the total number of corresponding repurchase opportunities.

$$SDRR = \frac{\#\,of\,stocks\,down\,since\,the\,sale\,repurchased}{\#\,of\,opportunities\,to\,repurchase\,stocks\,down\,since\,the\,sale} \quad (4.5)$$

$$SURR = \frac{\#\,of\,stocks\,up\,since\,the\,sale\,repurchased}{\#\,of\,opportunities\,to\,repurchase\,stocks\,up\,since\,the\,sale} \quad (4.6)$$

At the aggregate level, the test is the following: $H0_3 : SDRR - SURR = 0$.

We then calculate the number of stocks down (up) in price that were repurchased and the number of opportunities to repurchase stocks down (up) in price since the sale for each investor to compute the repurchase rates at the individual level.

$$SDRR_i = \frac{\#\,of\,stocks\,down\,since\,the\,sale\,repurchased\,for\,inv.\,i}{\#\,of\,opportunities\,to\,repurchase\,stocks\,down\,since\,the\,sale\,for\,inv.\,i} \quad (4.7)$$

$$SURR_i = \frac{\#\,of\,stocks\,up\,since\,the\,sale\,repurchased\,for\,inv.\,i}{\#\,of\,opportunities\,to\,repurchase\,stocks\,up\,since\,the\,sale\,for\,inv.\,i} \quad (4.8)$$

The average $\bar{D2}$ across investors is then computed as $\bar{D2} = \frac{1}{N}\sum D1_i$ with $D2_i = SDRR_i - SURR_i$, to test $H0_4 : \bar{D2} = 0$. $\bar{D2}$ is computed across investors for whom we observed at least one opportunity to repurchase a stock whose price declined and a stock whose price increased and that was sold during the previous year.

4.3.2 Survival analysis and repurchase behavior

Although the rates of repurchase have good statistical properties when aggregated over a large number of investors, the variables work less well at the individual level. This issue is pointed out by Feng and Seasholes (2005) in the context of the disposition effect. They demonstrate that the proportion of gains and losses realized are not efficient when computed by investor and should be avoided in cross-sectional studies. They show that these measures are correlated with the number of stocks held by investors. The same argument applies to the repurchase rates. Indeed, the small numbers of sales and repurchases generate large variation in the main variables of interest ($PWRR$, $PLRR$, $SURR$, $SDRR$). This variation is largely due to the number of repurchase opportunities, i.e., the number of sales in the past. This feature becomes an issue in the analysis of differences between different types of investors because their characteristics are directly linked to the number of repurchase opportunities. Actually, an investor with a more diversified portfolio has more repurchase opportunities just because he has held and sold more stocks in the past. A similar logic most likely applies to investors holding more foreign stocks as well. The number of repurchase opportunities determines the denominator in the repurchase rate and thus generates mechanical variation that has little to do with true difference between investors. We address this issue with hazard rate analysis.[10]

This methodology is close to a logit regression and provides a statistical model of how stocks are typically repurchased. Furthermore, we can interpret the changes in the repurchase duration due to a change in an independent variable. In a survival analysis, the duration prior to a hazard random event is regressed on independent variables called covariates. In our case, the hazard event is the repurchase of a stock. Hence, for each repurchase, the duration between the sale and the repurchase day is recorded. The survival function $S(t)$ represents the probability that a duration T passes before the occurrence of the random event. In other words, it is the probability that a repurchase occurs after time t.

$$S(t) = Prob(T \geq t) = 1 - F(t) \tag{4.9}$$

where $F(t)$ is the cumulative distribution function for T. The instantaneous probability of repurchasing a stock conditional on not having repurchased it is given by the hazard rate

$$h(t) = \lim_{\Delta_t \to 0} \left[\frac{(Prob(t \leq T < t + \Delta t | T \geq t))}{t} \right] = \frac{f(t)}{S(t)} \tag{4.10}$$

where $f(t)$ is the density function of T at time t. The hazard and survival functions computed when all covariates are equal to zero constitute the baseline hazard function and the baseline survival function. Following the results of the Schoenfeld residual tests, we reject the proportional hazard assumption. Hence, we estimate an

[10]See Harrell (2001) for a detailed description of survival analysis.

Accelerated Failure Time (AFT) model.[11] Here, the natural logarithm of the survival time is expressed as a linear function of the covariates, yielding the following linear model

$$log(t) = \alpha + X'\beta + \epsilon \tag{4.11}$$

where α is the intercept, X' is a vector of covariates, β is a vector of regression coefficients, and ϵ is the error with density $f()$. The distributional form of the error term determines the regression model. Based on the Akaike information criterion, we estimate a Weibull distribution for the error term.[12] The effect of the AFT model is to alter the rate at which repurchase occurs by a factor $e^{(-X'\beta)}$. More precisely, if a subject at baseline experiences a probability of survival after time t equal to $S(t)$, then a subject with covariates X' would have a probability of survival after time t equal to $S()$ evaluated at the point $e^{(-X'\beta)t}$ instead.

4.4 Repurchase behavior and sophistication: Empirical results

4.4.1 Repurchase behavior

Table 4.4 is dedicated to the repurchase rates of prior winners and losers. The first panel reports the aggregate results. The difference $PWRR - PLRR$ is positive and highly significant ($t = 61.2$). The second panel shows that $\bar{D}1 = 0.0362$, $t = 21$.

[11] Estimations are accomplished with maximum likelihood

[12] Choosing a log-normal or a log-logistic distribution does not impact the conclusions of our study.

Recall that $\bar{D1}$ is the average of $D1_i = PWRR_i - PLRR_i$ across investors. The seemingly large difference between individual results and aggregate results is linked to the computation of $PWRR$ and $PLRR$ for which the opportunities are cumulated over time. In this case, the difference between a sum of ratios and a ratio of sums can be large. Moreover, the difference between $PWRR_i$ and $PLRR_i$ is positive for 62.6% of investors ($t = 42.7$).

Therefore, our results allow us to reject $H0_1$ and $H0_2$; at both the aggregate and individual level, investors are more prone to repurchase stocks previously sold for a gain than they are to repurchase stocks previously sold for a loss. It is worth noting that the rejection of $H0_1$ and $H0_2$ is also obtained when the reference price is either the weighted average purchase price or the lowest purchase price of the stock.

We determine whether the previous sale constituted a gain or a loss based on the latest price that investors paid to acquire the asset. This process is consistent with the peak-and-end pattern established by Kahneman, Frederickson, Schreiber, and Redelmeier (1993); Fredrickson and Kahneman (1993) and Varey and Kahneman (1992). Indeed, investors remember only the latest and the lowest/highest price they paid for a stock. Based on the delay in studying past transactions set to one year, the most consistent reference price is the latest price. Yet, the concept of reference point is a complicated issue because this point might differ from one agent to another and even change over time. Other reference points are suggested in the literature. For example, Weber and Camerer (1998) and Grinblatt and Keloharju (2000) find that investors update their reference point with new prices when the purchase price is too old. Arkes, Hirshleifer, Jiang, and Lim (2008) find that investors adapt their reference points depending on their gains and losses.

Table 4.5 displays the results related to the preference for repurchasing stocks whose prices have declined since the previous sale. Panel A provides results of the aggregate repurchase rate of stocks down (up) since the sale, where $SDRR - SURR = 0.02641$ ($t = 289.3$). At the individual level (panel B), $\bar{D}2 = 0.08607$ ($t = 53.2$). We remind the reader that $\bar{D}2$ is computed by averaging $D2_i = SDRR_i - SURR_i$ across individuals. The preference for repurchasing stocks whose prices have declined since the sale is confirmed for 70.80% of our investors ($t = 79.4$). These results allow us to reject the hypotheses $H0_3$ and $H0_4$; at both the aggregate and individual level, investors are more prone to repurchase stocks whose prices have declined since the prior sale than stocks whose prices have increased since the prior sale.

The robustness of our conclusions is tested based on survival analysis methods. To evaluate whether investors tend to repurchase stocks they previously sold for a gain and stocks that have lost value since being sold, we include two key covariates in the model, namely *Winner* and *Down price*. The *Winner* dummy takes the value of 1 if the stock has been sold for a gain, and the *Down price* dummy takes the value of 1 if the stock price has declined since the sale.

Plots of the survival function functions are displayed in figure 4.2. The first graph is dedicated to the *Winner* indicator, and the second graph is dedicated to the *Down price* indicator. In both cases, the survival function decreases quickly, with 75% of the duration lasting less than 100 days. Notably, the graphs show that the duration period is lower for stocks sold for a profit (i.e., *Winner*=1) and stocks whose prices had declined since the sale (i.e., *Down price*=1). It is also worth mentioning that if a stock is sold for a profit, the average duration between the sale and a repurchase is 52.6 days, compared to 54.7 days if a stock is sold for a loss. The average time to repurchase for stocks whose prices had declined since the sale is 49 days, compared to 60 days for stocks whose prices had increased since the sale.

In what follows, we interpret the changes in the probability of repurchase due to a change (from zero to one) in the *Winner* and *Down price* variables. As we examine the repurchase behavior at the individual level, these regressions are computed with robust standard errors clustered at the investor level. Results are displayed in table 4.6. Both the *Winner* and *Down price* variables are statistically significant, corroborating our previous results. More precisely, the coefficient for *Winner* implies a hazard ratio equal to exp(-0.0334315)=0.967121. Therefore, when the *Winner* indicator is equal to 1, the duration between a sale and a repurchase is accelerated by 1-0.967121=0.032879, or 3.29%. When the *Down price* indicator is equal to 1, the duration is accelerated by 22%. Compared to an average duration baseline of 53.55 days (i.e., when covariates are not included in the model), this proportion corresponds to a reduction of more than 11 days.

These additional results confirm the existence of repurchasing behaviors on a large sample of French individual investors. In the following section, we examine the relationship between investors sophistication and repurchase preferences.

4.4.2 Impact of sophistication

Although it is clear that investor sophistication modifies behavior (Feng and Seasholes, 2005; Dhar and Zhu, 2006), no research has explored the impact of sophistication on repurchase references. Using direct and indirect proxies for sophistication, we investigate the existence of a link between repurchase behavior and sophistication.

To evaluate the influence of sophistication on repurchase patterns, we do not compare the averaged individual results (i.e., $\bar{D}1$ and $\bar{D}2$) between subsets. Instead, we start by conducting a test at the aggregate level. We compute the aggregate repurchase rates for each sophistication subset (i.e., *Two accounts=0, Two accounts=1; Diversification=0, Diversification=1; Foreign Stocks=0, Foreign stocks=1.* Results are presented in table 4.7. In each subsample, we observe a positive difference between the repurchase rates of prior winners and losers. The preference for repurchasing stocks whose prices have declined since the previous sale is also confirmed. Therefore, on average, investors exhibit both repurchase preferences regardless of their category (sophisticated or not). The difference in $D1$ (i.e., the preference for stocks previously sold for a gain) is higher for less sophisticated investors, confirming our intuition. For example, the computed $D1$ value for most diversified investors is 0.0049, and the computed $D1$ value for less diversified investors is 0.0162. Therefore, the first preference for the most diversified investors represents one third of the preference for less diversified investors. We obtain similar results for the second preference (i.e., the tendency to repurchase stocks whose prices have declined since the previous sale, as measured by $D2$) except for the diversification variable. This result would imply that investors who are the most diversified do not have a weaker tendency to repurchase stocks whose prices have declined since the previous sale. However, all other results suggest that sophistication attenuates the repurchase preferences.

Turning to the survival analysis, we present the results for the joint effect of *Winner* (*Down price*) with *Two accounts*, *Diversification* and *Foreign stocks* variables. To determine whether sophistication has an impact on repurchase preferences, interactions variables are included in the regression. Results are displayed in table 4.8. Regressions 1, 2, and 3 test the investor sophistication covariates separately, and Regression 4 tests all covariates together. Panel A is dedicated to the *Winner variable*. First, we find that all the coefficients are significant. For instance, an investor who trades on two accounts and has sold a stock for a profit (Regression 1) is less inclined to repurchase this stock than an investor who does not trade on multiple accounts. Indeed, the combined coefficient is (-0.1495972+0.2041783)=0.054581, which corresponds to a hazard ratio equal to exp(0.054581)=1.056098 and a decelerated repurchase duration of 5.6%. For investors who satisfy all the sophistication variables (Regression 4), the total decelerating effect is 15%. If we consider the average duration baseline (53 days), this proportion corresponds to 8 extra days. Therefore, the duration acceleration due to the *Winner* indicator is eliminated when this indicator interacts with sophistication variables.

Panel B is dedicated to the *Down price* variable. Focusing on Regression 2, we observe that an investor who is sorted in the top diversification quintile and has sold a stock whose price has declined since the previous sale is less inclined to repurchase this stock than an investor who is less diversified. The combined coefficients is 1-(exp(-0.3015876+0.072032))=20.51%, which corresponds to a lower acceleration of the repurchase duration than that observed (22%) when the sophistication covariates are not integrated. Similar results are observed in Regressions 1 and 3, with accelerations of.15.21% and 15%, respectively. For an investor who satisfies the three sophistication variables (Regression 4), the decrease in the repurchase duration corresponds to 5 days. Recall that when sophistication covariates are not included in the model, the average duration is reduced by more than 11 days. Contrary to the result reported in Panel A, sophistication diminishes, but does not eliminate, the duration acceleration.

Hence, the investors who we hypothesize are the most sophisticated suffer much less from the repurchase preferences than the average investor.

4.5 Further analysis

In this section, we test alternative motivations that could explain the repurchase behavior and propose a behavioral explanation.

4.5.1 Further tests of alternative motivations

Several standard motivations could explain the repurchase behavior of the investigated investors. First, each pattern could be motivated by superior skills or information. Second, the preference for the repurchase of stocks whose prices have declined since the previous sale could indicate a contrarian strategy.

To test whether repurchase preferences are motivated by private information, we begin by evaluating whether investors earn greater returns on their repurchase trades than on their buys and sales, following Odean (1999)s methodology. We consider horizons of T=3 months, 6 months and 1 year. To compute the ex-post average returns to securities repurchased (resp. purchased, sold) by the investor during the T trading periods subsequent to the trade, we index each transaction with a subscript i ($i = 1\, to\, N$). If the same stock is repurchased (resp. purchased, sold) in different accounts on the same day, each trade is counted as a distinct observation. The average return across all repurchases realized by all investors is computed as follows

$$Average\, return\, of\, stocks\, repurchased_T = \frac{1}{N}\sum_{i=1}^{N} R_{(j,i,i+T)} \tag{4.12}$$

where $R_{(j,i,i+T)}$ is the return of stock j between day i and $i+T$. The average returns of stock purchases and sales are computed similarly.

The results for the entire sample are presented in table 4.9. The difference between the ex post average return of repurchases and purchases is negative, as is the difference between the ex-post average return of repurchases and sales. This result indicates that the stocks repurchased by investors are less profitable than the stocks bought and sold during the same period. To compare the average returns during subsequent periods, a classical test of means, which requires independence in the observations, cannot be run.[13] In short, because returns are averaged during the trading histories of investors and across investors, the returns can overlap. Thus, statistical significance is estimated by conducting a Wilcoxon test of differences. The average ex post return on repurchased stocks (resp. purchased, sold) is determined for each investor separately during the three chosen horizons T (T=three-month, six-month and one-year). We then compute the distribution of all individual average returns for repurchased, purchased and sold stocks. We compare these distributions using the Wilcoxon test. More formally, we first test whether the repurchase returns and purchase returns samples come from populations with the same median and the same continuous distribution. Second, we compare the repurchase returns sample with the sale returns sample.

The null hypothesis is rejected regardless of the period under consideration, suggesting that the distributions of the average returns of repurchased and purchased securities are significantly different. Similarly, the test indicates that the distributions of the returns of stocks repurchased and sold are reliably different.

[13] Actually, a security can be traded by different investors on more than one date. For example, an investor can buy one stock on date t and another can repurchase the same stock 2 weeks later. A third investor can sell the stock the day after. Because ex post returns are estimated on three-month, six-month and one-year horizons, the returns of the stock traded in these three cases are not independent. A security may also be traded by the same investor on the same day.

If the preference for the repurchasing of stocks previously sold for a gain (resp. a preference for stocks whose prices have declined since the previous sale) is driven by superior skills or private information, we should observe that repurchases outperform buys and sales. The results in Panels B and C (table 4.9) show that repurchased stocks are less profitable than the bought and sold stocks, proving that investors with a positive $D1_i$ and investors with a positive $D2_i$ do not repurchase stocks based on private information.

We control the robustness of our conclusion by an analyzing the portfolio performance of investors prone to one (or both) repurchase behavior. We choose to partition investors based on the sign of their repurchase patterns. On one hand, we focus on investors who exhibit a preference for the repurchasing of stocks previously sold for a gain. We isolate investors who exhibit a preference for repurchasing stocks whose prices have declined since the previous sale. Recall that 62.6% of investors exhibit a positive $D1_i$ and 70.8% of investors exhibit a positive $D2_i$. These investors are coined positive preference investors. On the other hand, we partition investors who exhibit an opposite behavior. We call these investors negative preference investors. Finally, we examine investors who are not prone to such repurchase patterns. Only 2.03% (resp. 1.47%) of investors exhibit a null $D1_i$ (resp. $D2_i$) and have no repurchase preference. Thus, for each preference, investors are segmented into 3 groups.

We compute the monthly returns of individual investors from January 2001 to December 2006. A mean return across investors is calculated each month to create a time series of 72 monthly returns.[14] In the first case, we compute the monthly return time series with an equal weight of individual investors to work on the average household level

$$Average\,Monthly\,Return = \frac{1}{N}\sum_{i=1}^{N} Monthly\,Return_{i,t} \tag{4.13}$$

where $i$denotes the investor, t denotes the month, and N denotes the number of investors.

$$Aggregate\,Monthly\,Return = \frac{1}{\sum PV_{i,t}}\sum_{i=1}^{N} Monthly\,Return_{i,t} * PV_{i,t} \tag{4.14}$$

To estimate the portfolio performance of investors, we first use Jensens alpha by regressing the monthly excess return earned by individual investors on the market excess return. The value-weighted market index is given by the Eurofidai general index (calculated using the methodology of the Center for Research in Security Prices (CRSP)). This index is based on approximately 700 stocks during the period under consideration. We estimate the following monthly time-series regression

$$Rp_t - rf_t = \alpha_p + \beta_p(Rm_t - rf_t) + \epsilon_t \tag{4.15}$$

where Rp_t is the average (aggregate) monthly return of investors, Rm_t is the monthly

[14]To be considered in the computation of the monthly average, an investors account must be open during the entire month. Actually, some investors opened an account within the 20012006 period, whereas others closed their account before the end of the period. On average, 26,532 over 34,129 investors per month have an open account, with a minimum of 23,224 in December 2006 and a maximum of 29,186 in April 2003. Of the 34,129 investors, 53.6% have an open account during the entire period of our dataset, and the average length of presence is 56 months (4.5 year).

return on the market index,$_p$ is the market beta, rf_t is the monthly risk free rate and corresponds to the 1-month Euribor, and $_t$ is the regression error term.

In a second step, we employ an intercept test using the three-factor model developed by Fama and French (1993)

$$Rp_t - rf_t = \alpha_p + \beta_p(Rm_t - rf_t) + z_p SMB_t + h_p HML_t + \epsilon_t \tag{4.16}$$

where SMB_t is the monthly return on a value-weighted portfolio of small stocks minus the monthly return on a value-weighted portfolio of large stocks, and HML_t is the monthly return on a value-weighted portfolio of high book-to-market stocks minus the monthly return on a value-weighted portfolio of low book-to-market stocks. z_p and h_p are coefficients on factor size and book-to-market. The SMB_t and HML_t factors are provided by Eurofidai and calculated using the Fama and French (1993) methodology.

The portfolio performance of the subsets based on the $D1_i$ and $D2_i$ signs are shown in table 4.10. Panel A (resp. B) displays the regression intercepts relative to the subsets based on the $D1_i$ (resp. $D2_i$) values. The first column contains the results obtained relative to positive preference investors, whereas the second column concerns negative preference investors. The third column is devoted to the results relative to investors who do not exhibit repurchase biases. All the intercepts are negative, revealing the poor performance of individual investors regardless of the directions of their preferences. However, the dominance of the alphas for investors who exhibit $D1_i = 0$ and/or $D2_i = 0$ should be emphasized. Actually, both the CAPM and the FamaFrench intercepts are higher compared with those computed on investors who exhibit $D1_i > 0$ and/or $D2_i > 0$. This result is significant in most cases. Therefore, investors who are unaffected in their repurchase decisions by past price patterns outperform investors whose repurchase trades are based on emotional incentives. Actually, this outperformance seems to primarily be the result of the frequency of investor trading. Indeed, the non-biased investors are less active than their peers. First, their average number of repurchases (equal to 3) is 10 times lower than the average for the entire sample. Second, their average monthly turnover is 12%, compared with 20.7% for the entire sample. It is well documented in the literature that excessive trading affects portfolio performance in a negative direction[15] and that individual investors are more successful at applying a buy-and-hold strategy. Thus, we infer that our result is directly linked to this assessment. Yet, this subset contains less than a handful of investors. In fact, investors are primarily sorted into either the positive preference subset or the negative preference subset. To infer how documented patterns of repurchasing affect portfolio performance, it is more appropriate to compare the results obtained from these subsamples.

The comparison between the alphas relative to positive and negative preference investors is much less clear. In fact, the signs of the differences between intercepts are negative but insignificant in almost all cases. Consequently, both directions in preferences similarly affect performances. In other words, the preference for the repurchasing of stocks previously sold for a gain and/or the repurchasing of stocks whose prices have declined since the sale has no particular effect on portfolio returns compared with the opposite behavior. This result corroborates our previous conclusion.

[15]See for example: Barber and Odean (1999, 2000); Barber, Lee, Liu, and Odean (2009); Odean (1999).

Biased investors not only fail to exhibit better ex post returns on their repurchases than on others trades, but their portfolio performance is also not higher than those of their peers. To test the second hypothesis, according to which investors apply a

contrarian strategy, we focus on investors who exhibit a preference for repurchasing stocks whose prices have declined since their sales $D2_i > 0$ and examine the past returns of the purchased stocks that were not sold during the previous year. The equally weighted cumulative market-adjusted ex post return on the past 252 days is displayed in figure 4.3. On average, the previous years market-adjusted return of stocks rises continuously to 13.4%. This group of investors seems not to tend to purchase stocks with poor recent performance. In accordance with Barber, Odean, and Zhu (2009b), we find that investors apply a momentum strategy in their purchases. Indeed, the cumulative market-adjusted returns before purchase are strongly positive. Thus, the preference for stocks with poor recent performances is dedicated to stocks previously owned and sold. The conclusions drawn from an experimental investigation on repurchase selection (Weber and Welfens, 2011) corroborate this additional result. To summarize, investors prone to the documented repurchase preferences do not exhibit better ex post returns on their repurchases than on their other trades and do not apply a contrarian strategy. Therefore, both motivations are not able to explain the observed patterns.

4.5.2 Behavioral motivations

Strahilevitz, Odean, and Barber (2011) propose an emotion-driven hypothesis, arguing that these repurchase patterns are mainly motivated by an investors desire to avoid regret. Two types of regret can be defined, and each affects repurchase behavior. The first one, induced by counterfactual thinking, is known as "experienced regret" because it is felt after decisions. Roese (1997) defines counterfactual thinking as mental representations of alternatives of the past. Literally, counterfactual means "contrary to the facts" and concerns an event that could have happened but did not. Agents compare the outcome resulting from their choice with what they would have if they selected the option they rejected. If the comparison is disadvantageous, the regret is triggered. To illustrate this situation, consider the case of not having bought a stock when the price was lower. This decision is likely to provoke retrospective thoughts such as "what if I bought it before?" Experienced regret influences repurchase decisions when an investor sells a particular stock that induces a loss. Her memories associated with this sale are so unpleasant that she definitely wants to erase them from her mind. Thus, she behaves as if this investment option no longer exists, and, consequently, she no longer trades these shares (Arkes, Kung, and Hutzel, 2002).

The second type of regret is known as "anticipated regret" [16] because it is an expected feeling. For example, this regret appears when foreseeing a purchase at a higher price compared with a previous missed opportunity (Tykocinski and Pittman, 1998). Prefactual thoughts such as "what if I find cheaper again?" appear before decisions and influence choices (McConnell, Niedermeierand, Leibold, El-Alayli, Chin, and Kuiper, 2000). In the context of stock repurchasing, the investor compares the

[16] Anticipated regret has been modeled with regret theory (Loomes and Sugden, 1982), which proposes an alternative theory to the classical model. For regret theory, expected utility depends on satisfaction over an agents own choice and on the utility of the outcomes that she could have obtained.

price at which she previously sold the asset with the current price. If the latter is higher, a repurchase would emphasize the fact that the investor could have performed better if she had waited to sell. The anticipation of a more intense regret caused by the notion that she would pay more to repurchase the asset than the amount she received with the sale will drive her to ignore this investment opportunity (Tykocinski and Pittman, 1998). Whereas investors attempt to avoid trades that reinforce negative emotions such as regret, they seek trades that reinforce positive ones such as pride. Therefore, they are more prone to repurchase stocks previously sold for a profit than those previously sold for a loss.

Investors behavior conditioned by regret are also consistent with reinforcement learning, through which personally experienced outcomes are overweighed compared with Bayesian learning. The reinforcement learning theory predicts that the effect on the future behavior of a directly realized payoff is greater than the same information without personal involvement. In the case of a repurchase, repeating the action (purchasing the same stock again) is conditioned on the outcome resulting from past experiences. With the reinforcement learning theory, the decision is simply based on the following rule: "win: stay, lose: switch" (Kaustia and Knupfer, 2008). An empirical test of this theory has already been provided by Kaustia and Knupfer (2008) in the context of IPO subscriptions. Their work underlines the importance of the initial experience, known in psychology as the primacy effect (Asch, 1946).

In line with the reinforcement learning hypothesis, an additional explanation for the repurchase patterns lies in what follows. Investors could simply be learning about their ability to analyze each stock. If they lose money on a stock, their estimate of their ability to make money on that stock falls. If they make money on a stock, their estimate of their ability to understand the firm rises, leading them to repurchase that security. The same argument applies to the preference for stocks whose prices have declined since the sale. However, it is worth noting that Weber and Welfens (2011) and Strahilevitz, Odean, and Barber (2011) provide evidence that this perceived-skills effect does not drive the tendency to repurchase stocks that have dropped in price since the sale. Although we do not refute that investors might make incorrect inferences about their abilities, their results support our conviction that investors mainly favor trades that reduce regret.

4.6 Conclusion

We highlight two patterns of repurchase behavior at the individual and aggregate levels. First, investors are more prone to repurchase stocks that they previously sold for a gain than they are to repurchase stocks that they previously sold for a loss. This preference for stocks previously sold for a gain can be explained by the tendency of investors to make trades that intensify positive emotions and reduce painful ones, such as experienced regret. Second, investors are more prone to repurchase stocks that have lost value than they are to repurchase those that have gained value since the prior sale. If the observed price has declined since the sale, the investor is prone to feel proud because she made a timely decision. On the contrary, if the price has increased, the consideration of this stock as an investment opportunity is unpleasant because the current price reminds the investor that she could have performed better by selling later. Therefore, the investor anticipates that the repurchase will yield regret and (unconsciously) chooses to ignore this stock.

Next, based on our original clustering with on direct measures, we show that more sophisticated investors are less prone to repurchase preferences. We conclude that sophisticated investors are endowed with financial skills that help them weaken the role of emotions in trades and, consequently, their behavioral bias.

Finally, we find that investors prone to repurchase biases do not exhibit higher ex post returns on their repurchases compared with their other trades. Moreover, their portfolio performance is not better than that of their peers, indicating that the documented behavior is not driven by superior skills or private information. Although the preference for the repurchase of stocks whose price declined since the sale suggests a contrarian strategy, this suggestion is not confirmed by the purchases. In conclusion, standard motives do not yield this behavior, which corroborates the behavioral hypothesis.

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Figure 4.1
Time axis

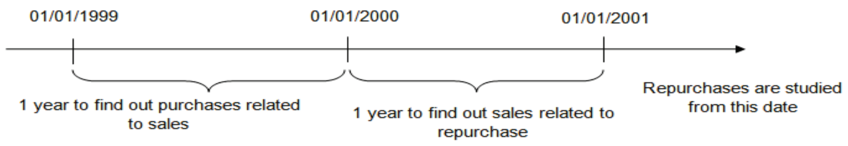

Figure 4.2
Survival analysis - Plots of survival functions

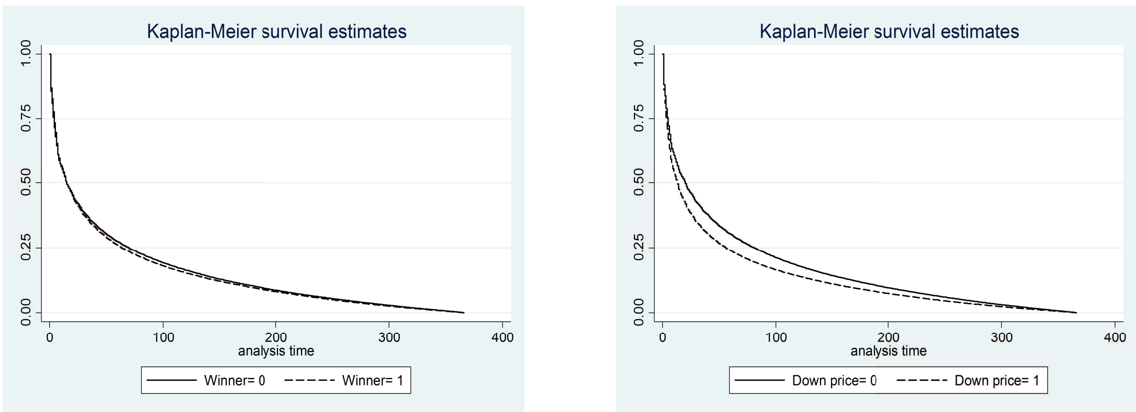

Figure 4.3
Cumulative market adjusted return prior to purchase

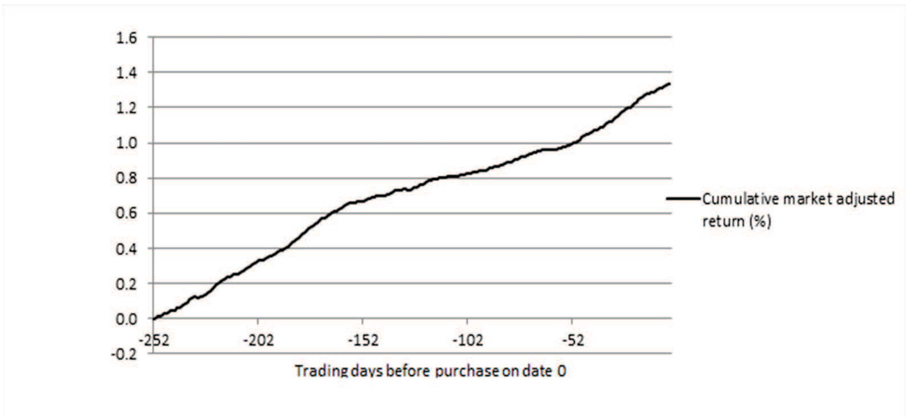

Table 4.1
Descriptive statistics

	Entire dataset	Investors who repurchased at least once
Panel A: Sample size		
Number of investors	84,500	34,129
Number of trades	8,072,016	6,885,276
Panel B: Trading behavior per investor		
Average number of trades	94 (23)	202 (85)
Average number of shares traded (per trade)	211 (55)	355 (108)
Average trade size (Euros)	2,640 (1,557.8)	3,396 (2,108.7)
Average purchase turnover (%)	14.9 (5.2)	22.8 (10.7)
Average sale turnover (%)	13.6 (4.8)	21.2 (10)
Average number of years of activity	3.7 (3)	5.1 (5)
Average delay between 2 trades (Days)	52.35 (26.64)	38 (28)
Average number of different assets in portfolio	4.8 (3)	7 (4.7)

This table presents statistics on the entire dataset, i.e., the 84,500 investors during the period 19992006, and on the sample of 34,129 investors who repurchased at least once. Panel A reports the number of investors and the number of trades. Panel B provides information on trading behavior per investor. The number of trades is the number of transactions realized per investor. The number of shares traded is calculated per investor and per trade. The trade size is computed as the quantities traded multiplied by the prices of the stocks traded. The purchase and sale turnovers are averaged across monthly turnovers. The monthly turnover is computed as the market value of shares purchased or sold in month t divided by the mean market value of all shares held in the portfolio during month t. The number of years of activity is the number of years that investors own active accounts. Active accounts are those with at least one transaction during one year. The delay between 2 trades is the number of business days between 2 consecutive trades. Medians are reported in parentheses.

Table 4.2
Investors sophistication - binary variables

Variables	Description	Frequency in the sample
	Panel A: Variables	
Diversification	= 1 if the investor is sorted in the top diversification quintile during the 1999-2006 period, 0 elsewhere	20%
Foreign stocks	= 1 if the investor is sorted in the top foreign stocks quintile during the 1999-2006 period, 0 elsewhere	20%
Two accounts	= 1 if the investor traded on multiple kind of accounts during the 1999-2006 period, 0 elsewhere	47.41%
	Panel B: Combined variables	
Diversification & Foreign stocks	= 1 if the investor is sorted in the top diversification quintile and in the top foreign stocks quintile during the 1999-2006 period, 0 elsewhere	8.20%
Diversification & Two accounts	= 1 if the investor is sorted in the top diversification quintile and if the investor traded on multiple kind of accounts during the 1999-2006 period, 0 elsewhere	14.44%
Foreign stocks & Two accounts	= 1 if the investor is sorted in the top foreign stocks quintile and if the investor traded on multiple kind of accounts during the 1999-2006 period, 0 elsewhere	10.82%
Diversification & Foreign stocks & Two accounts	= 1 if the investor is sorted in the top diversification quintile and in the top foreign stocks quintile and if the investor traded on multiple kind of accounts during the 1999-2006 period, 0 elsewhere	5.85%

This table presents the definitions and frequencies of the sophistication binary variables in the subsample of 34,129 investors who repurchased at least once. Panel A is dedicated to variables *Diversification, Foreign assets and Two accounts* alone. Panel B presents the frequencies of investors who satisfy more than one sophistication criterion.

Table 4.3
Measures of association between binary variables

	Pearson Chi-squared	**Cramer**
Two accounts & foreign stocks	364 ***	10.34%
Diversification & Two Accounts	2200***	25.25%
Foreign stocks & Diversification	2900***	29.08%

This table contains measures of association (Pearson Chi-squared and Cramer coefficients) between sophistication binary variables for the 34,129 investors in the selected sample. ***, ** and * indicate that the results are significant at the 1%, 5% and 10% levels, respectively.

Table 4.4
Preference for stocks previously sold for a gain versus stocks previously sold for a loss

Panel A: Aggregate results (34,129 investors)	
Winners repurchased	534,807
Opportunities to repurchase winners	12,366,035
$PWRR$	0.04325
Losers repurchased	236,348
Opportunities to repurchase losers	6,336,547
$PLRR$	0.0373
$D1 = PWRR - PLRR$	0.00595 ***
t-test	61.2
Panel B: Individual results (26,964 investors)	
$\bar{D1}$	0.03620 ***
t-test	21
Proportion of investor for whom $PWRR_i > PLRR_i$	62.6% ***
t-test	42.7

This table presents aggregate and individual results for the test dedicated to the preference of stocks previously sold for a gain versus stocks previously sold for a loss. The first panel reports the difference $D1$ between the aggregate Repurchase Rate of Prior Winners $PWRR$ and the aggregate Repurchase Rate of Prior Losers ($PLRR$) of 34,129 investors between 2001 and 2006. Winners and losers are defined according to the outcome of sales that occurred in the previous year. $PWRR$ is the ratio of the number of winners repurchased over the number of opportunities to repurchase winners. $PLRR$ is computed in a similar way. Opportunities correspond to stocks that have been sold in the previous year and are not repurchased. The second panel shows the average $\bar{D1} = \frac{1}{26964}(\sum_{i=1}^{26964} D1_i)$, with $D1_i = PWRR_i - PLRR_i$. Among our initial population of 34,129 investors, only those who had at least one opportunity to repurchase a previous winning stock and a previous losing stock are considered. T-tests related to the hypotheses $H0_1 : D1 = 0$ and $H0_2 : \bar{D1} = 0$ are reported in the last rows. ***, ** and * indicate that the results are significant at the 1%, 5% and 10% levels, respectively.

Table 4.5
Preference for stock up since being sold versus stock down since being sold

Panel A: Aggregate results (34,129 investors)	
Stocks down repurchased	474,242
Opportunity to repurchase stocks down	8,451,614
$SDRR$	0.05611
Stocks up repurchased	321,914
Opportunity to repurchase stocks up	10,837,871
$SURR$	0.02970
$D2 = SDRR - SURR$	0.02641 ***
t-test	289.3
Panel B: Individual results (30,185 investors)	
$\bar{D}2$	0.08607 ***
t-test	53.2
Proportion of investor for whom $SDRR_i > SURR_i$	70.8% ***
t-test	79.4

This table presents aggregate and individual results for the test dedicated to the preference of stocks whose prices have declined since the previous sale versus stocks whose prices have increased since the previous sale. The first panel reports the difference $D2$ between the aggregate Rate of Stocks Down since the sale Repurchased ($SDRR$) and the aggregate Rate of Stocks Up since the sale Repurchased ($SURR$) of 34,129 investors between 2001 and 2006. Up and down stocks are defined according to the change in stock price since the sale. $SURR$ is the ratio of stocks whose price has increased since the sale repurchased over opportunities to repurchase stocks whose price has increased since the sale. $SDRR$ is computed in a similar way. Opportunities correspond to stocks that have been sold during the previous year and are not repurchased. The second panel shows the average $\bar{D}2 = \frac{1}{30185}(\sum_{i=1}^{30185} D2_i)$, with $D2_i = SDRR_i - SURR_i$. Among our initial population, only investors who had at least one opportunity to repurchase a stock whose price has declined and a stock whose price has increased since the sale are considered. T-tests related to the hypotheses $H0_3 : D2 = 0$ and $H0_4 : \bar{D}2 = 0$ are reported in the last rows. ***, ** and * indicate that the results are significant at the 1%, 5% and 10% levels, respectively.

Table 4.6
Repurchase preferences - Survival analysis

	Regression 1	**Regression 2**
Winner	-0.0334215 ***	
	(-4.1)	
Down price		-0.2482651 ***
		(-23.9)
p **parameter**	0.6275829	0.6291078
Number of observations	796,601	796,601
Chi2 statistics	16.4	569.9

This table presents the estimation results of the accelerated failure time model. We use a Weibull distribution with parameter p to parameterize the hazard function. The dependent variable is the duration between a sale and the repurchase of the stock sold. In regression 1, the independent variable *Winner* is an indicator that takes a value of 1 if the stock has been previously sold for a gain. In regression 2, the independent variable *Down price* is an indicator that takes a value of 1 if the stocks price has declined since the sale. Z-stats are in parentheses. Regressions are computed with robust standard errors clustered at the investor level. ***, ** and * indicate that the results are significant at the 1%, 5% and 10% levels, respectively.

Table 4.7
Repurchase preferences and sophistication - Aggregate results

	Diversification		***Two accounts***		***Foreign stocks***	
	1	0	1	0	1	0
D1	0.0049 ***	0.0162 ***	0.0052 ***	0.0068***	0.0029 ***	0.0092 ***
t test	49.1	66.7	43.3	44.6	25.2	60.9
D2	0,0247***	0,0243 ***	0.0249 ***	0.0269 ***	0.0196 ***	0.0318 ***
t test	246.3	101.7	210.8	175.1	170	211.9

This table presents the results of the repurchase behavior tests realized on sophistication subsamples *Diversification=1, Diversification=0; Two accounts=1, Two accounts= 0; Foreign stocks=1; Foreign stocks=0.* $D1 = PWRR - PLRR$ and $D2 = SDRR - SURR$ are computed for each subset. $PWRR$ ($PLRR$) is the aggregate Repurchase Rate of Previous Winners (Losers), and $SDRR$ ($SURR$) is the aggregate Repurchase Rate of Stocks Down (Up) in price since the sale. Winners and losers are defined according to the outcome of sales that occurred in the previous year. $PWRR$ is the ratio of number of winners repurchased over number of opportunities to repurchase winners. $PLRR$ is computed in a similar way. Opportunities correspond to stocks that have been sold in the previous year and are not repurchased. Up and down stocks are defined according to the change in the stock price since the sale. $SURR$ is the aggregate ratio of stocks repurchased whose price has increased since the sale over the opportunities to repurchase stocks whose price has increased since the sale.$SDRR$ is computed in a similar way T-stats control for the significance of results. ***, ** and * indicate that the results are significant at the 1%, 5% and 10% levels, respectively.

Table 4.8
Repurchase preferences and sophistication - Survival analysis

	Regression 1	**Regression 2**	**Regression 3**	**Regression 4**
		Panel A: $D1_i$		
Winner	-0.1495972***	-0.2094198***	-0.0999664***	-0.28344***
	(-8.8)	(11.3)	(-8.3)	(-13)
Two Accounts * Winner	0.2041783***			0.1633533***
	(7.5)			(5.9)
Diversification * Winner		0.2304401***		0.1435127***
		(10.3)		(5.8)
Foreign stocks * Winner			0.1648788***	0.1175731***
			(5.6)	(3.7)
p parameter	0.6283178	0.628293	0.6279725	0.6288766
Number of observations	796601	796601	796601	796601
Chi2 statistics	78.2	128.1	69.8	186
		Panel B: $D2_i$		
Down price	-0.3565343***	-0.3015876***	-0.3044584***	-0.3879939***
	(-19.9)	(16.5)	(-22.5)	(-17.8)
Two Accounts * Down price	0.1914597***			0.1868915***
	(6.4)			(6.2)
Diversification * Down price		0.072032***		-0.0252133
		(-2.9)		(-0.9)
Foreign stocks * Down price			0.1418486***	0.1330481***
			(4.4)	(3.8)
p parameter	0.6296796	0.629152	0.6293462	0.62988
Number of observations	796601	796601	796601	796601
Chi2 statistics	676.9	669.9	711.2	874

This table presents the estimation results of the accelerated failure time model. We use a Weibull distribution with parameter p to parameterize the hazard function. The dependent variable is the duration between a sale and the repurchase of the stock sold. In panel A, the independent variable *Winner* is an indicator that takes a value of 1 if the stock has been previously sold for a gain. In panel B, the independent variable *Down price* is an indicator that takes a value of 1 if the stocks price has declined since the sale. We interact each indicator variable with 3 sophistication dummies to measure cross-sectional differences in investors propensity to repurchase stocks sold for a profit/whose price declined since the sale. *Diversification* takes a value of 1 if the investors diversification level is in the top quintile of the diversification level. *Foreign stocks* takes a value of 1 if the investors number of stocks from different countries in the portfolio is in the top quintile of the number of stocks from different countries in portfolios. *Two accounts* takes a value of 1 if the investor trade on two kind of accounts. Z-stats are in parentheses. Regressions are computed with robust standard errors clustered at the investor level. ***, ** and * indicate that the results are significant at the 1%, 5% and 10% levels, respectively.

Table 4.9
Ex-post returns on purchase/repurchase/sale trades

	Repurchases	**Purchases**	**Sales**	**Repurchases -Purchases**	**Repurchases -Sales**
		PANEL A: Whole sample			
Number of trade	796,601	1,685,892	2,287,581		
3 months	0.30	0.80	1.33	-0.5 *** (18.9)	-1.03 *** (43.3)
6 months	1.57	2.38	3.04	-0.81 *** (18.7)	-1.47 *** (45.9)
1 year	6.47	7.53	8.26	-1.06*** (21.6)	-1.78 *** (47.3)
		PANEL B: Positive $D1_i$ investors			
Number of trades	791,657	1,653,247	2,256,600		
3 months	0.34	0.82	1.30	-0.48*** (15.2)	-0.96 *** (42.3)
6 months	1.64	2.42	3.01	-0.78 *** (14.8)	-1.36 *** (45)
1 year	6.57	7.60	8.21	-1.03 *** (18.5)	-1.64 *** (43.7)
		PANEL C: Positive $D2_i$ investors			
Number of trades	782,754	1,595,266	2,202,143		
3 months	0.33	0.84	1.35	-0.51 *** (17.3)	-1.01 *** (42.3)
6 months	1.63	2.45	3.07	-0.82 *** (17.3)	-1.44 *** (45.1)
1 year	6.55	7.64	8.30	-1.08 *** (20.6)	-1.74 *** (46)

Average ex-post returns are calculated for the 3-month, 6-month and 1-year horizons following purchases, repurchases and sales of 34,129 investors between 1999 and 2006. Panel A reports results for the whole sample. Panels B and C present results for the subsamples of investors who exhibit a positive $D1_i = PWRR_i - PLRR_i$ and a positive $D2_i = SDRR_i - SURR_i$. $PWRR$ ($PLRR$) is the Repurchase Rate of Previous Winners (Losers), and $SDRR$ ($SURR$) is the Repurchase Rate of Stocks Down (Up) in price since the sale. Winners and losers are defined according to the outcome of sales that occurred in the previous year. $PWRR$ is the ratio of the number of winners repurchased over the number of opportunities to repurchase winners. $PLRR$ is computed in a similar way. Opportunities correspond to stocks that have been sold in the previous year and are not repurchased. Up and down stocks are defined according to the change in stock price since the sale. $SURR$ is the ratio of stocks repurchased whose price has increased since the sale over the opportunities to repurchase stocks whose price has increased since the sale. $SDRR$ is computed in a similar way Statistical significance is tested with a non-parametric Wilcoxon rank sum test. Z-values are presented in parentheses, and ***, **, * indicate that results are significant at the 1%, 5% and 10% levels, respectively.

Table 4.10
Portfolio performance of subsets formed on $D1_i$ and $D2_i$ signs

	Positive	Negative	Null	Pos.-Neg.	Pos.-Null
			Panel A: $D1_i$		
			Intercept estimations for the average investor		
CAPM	-0.56	-0.58	-0.52	0.02	-0.04
t-test	-1.5	-1.6	-1.5	0.3	-0.6
Fama-French	-0.76 *	-0.74 *	-0.66 *	-0.02	-0.08 *
t-test	-1.9	-1.8	-1.7	-0.2	-1.4
			Intercept estimations for the aggregate investor		
CAPM	-0.64 *	-0.59	-0.21	- 0.05	-0.43 ***
t-test	-1.8	-1.6	-0.8	-0.8	-8.5
Fama-French	-0.83 **	-0.77 *	-0.34	-0.06	-0.49 ***
t-test	-2.1	-1.9	-1.3	-0.8	-8.7
			Panel B: $D2_i$		
			Intercept estimations for the average investor		
CAPM	-0.55	-0.50	-0.50	-0.05	-0.05
t-test	-1.5	-1.4	-1.3	-0.8	-1
Fama-French	-0.69 *	-0.76 *	-0.57	0.07	-0.12 *
t-test	-1.7	-1.9	-1.3	1	-1.7
			Intercept estimations for the aggregate investor		
CAPM	-0.64 *	-0.40	-0.29	-0.24 ***	-0.35 ***
t-test	-1.8	-1.2	-0.9	-4.1	-6.3
Fama-French	-0.80 **	-0.70 *	-0.41	-0.10	-0.39 ***
t-test	-2	-1.9	-1.2	-1.6	-6.2

This table reports percentage estimations intercept for the datasets of investors who exhibit positive, negative and null repurchase preferences. Panel A presents the regression intercepts relative to the samples based on $D1_i = PWRR_i - PLRR_i$ values, and Panel B presents the alphas relative to the samples based on $D2_i = SDRR_i - SURR_i$ values. $PWRR$ ($PLRR$) is the Repurchase Rate of Previous Winners (Losers) and $SDRR$ ($SURR$) is the Repurchase Rate of Stocks Down (Up) in price since the sale. Winners and losers are defined according to the outcomes of sales that occurred in the previous year. $PWRR$ is the ratio of the number of winners repurchased over the number of opportunities to repurchase winners. $PLRR$ is computed in a similar way. Opportunities correspond to stocks that have been sold in the previous year and are not repurchased. Up and down stocks are defined according to the change in the stock price since the sale. $SURR$ is the ratio of stocks whose price has increased since the sale repurchase over the opportunities to repurchase stocks whose price has increased since the sale. $SDRR$ is computed in a similar way. The CAPM intercept is the estimated intercept from a time-series regression of the investor excess return on the market excess return. The FamaFrench intercept is the estimated intercept from time-series regressions of the investor excess return on the market excess return, a zero-investment book-to-market portfolio (HML), and a zero-investment size portfolio (SMB). The average investor results are computed based on a time series of equally weighted average returns. The aggregate investors results are computed based on a time series of value weighted average returns.

Conclusion

The contributions of this PhD dissertation are both methodological and empirical.

The first chapter is dedicated to the analysis of trading performance of French individual investors. Though their trading performance has been examined in a several countries (Barber and Odean, 2000; Grinblatt and Keloharju, 2000), there is no empirical evidence for France. Hence, the first contribution of this chapter is to fill this gap in the literature. We provide evidence that French investors exhibit gross and net negative risk adjusted returns. Moreover, we show that they would be better off investing in the market index instead of actively managing their wealth. Indeed, they take suboptimal decisisons, such as purchasing stocks that underperform the ones they sell. We take advantage of the three sub-periods in our database (dot-com bubble, post-internet bubble and 2003-2006 bullish years) and show that this sub-profitability is observed under each market trend. Our second contribution is to examine whether more sophisticated investors are more successful in their trading performance compared to less sophisticated investors. Researchers show that individual characteristics such as I.Q., gender, age or wealth can explain the cross-sectional variations in performance but the role of sophistication is still unexplored. We rely on existing evidence regarding sophistication metrics and consider investors to be sophisticated if they hold diversified portfolios, trade foreign assets and use multiple accounts to trade. The last indicator is based on a specific French fiscal feature. Investors trading on two types of accounts are sophisticated because they take advantage of both a standard account and a tax-free account (i.e., a French PEA). We provide evidence that sophisticated investors do not outperform their peers.

The second chapter of this dissertation deals with the cross-section of investors performance. In opposition to classic analysis which examine the impact of observable variables, we analyze whether the variations in performances can be traced to latent investors' aspiration levels. In this chapter, aspirations are evaluated according to the Behavioral Portfolio Theory (Shefrin and Statman, 1985) in which investors consider their portfolio as a pyramid of assets. The riskless are in the bottom layers and the riskier on the top. Each layer is associated to an aspiration level, i.e., a wealth level that the investor wants to achieve for a specific goal (bequest, retirement, holidays, etc.). Following Shefrin (2005), we consider that investors who trade derivatives have high aspiration levels, whereas investors who trade bonds have low aspirations. We highlight two profiles of investors based on the securities they trade. Investors who have low aspiration levels hold more diversified and less-risky portfolios than investors who have high aspiration levels. The latter trade more frequently. We contribute to the research dedicated to explaining factors of portfolio performance by comparing risk-adjusted returns of investors who have high/low aspiration levels. We show that high aspiration investors underperform their peers whereas low aspiration investors outperform their peers. Our main finding is that standard determinants of variation in performance such as risk factors, diversification and turnover, do not significantly influence our results.

In the third chapter, we analyze the importance of the measure chosen to evaluate individual investors performance. Similar studies have been conducted on funds (Zakamouline, 2011), but this issue has not been raised for individual investors. We contribute to that stream of literature by focusing on portfolios of individual investors. Based on a theoretical development, we argue that the poor performances of individual investors are due to an ill-suited performance measure. Indeed performances are usually computed using classic measures such as the Sharpe ratio. Yet standard measures suffer from multiples weaknesses when it comes to evaluate individual investors. We choose five alternative measures of performance that address the Sharpe ratio drawbacks. In these measures, the risk is defined as negative deviations of returns from a benchmark (i.e. the downside risk). Moreover, alternative ratios convey different hypotheses regarding investors behavior: Loss aversion, Expected Utility Theory, Prospect Theory and Behavioral Portfolio Theory.

This chapter contains several empirical findings. First, we show that the choice of the measure influences the evaluation of investors. Indeed, the rank permutations from the Sharpe ratio to alternative measures evaluations are significant. Second we show that, when comparing investors' portfolio to the market index with alternative ratios, rather than with the Sharpe ratio, they are not such poor portfolio managers. Notably, with the alternative measure fitting the Behavioral Portfolio Theory, a larger part of investors beat the market. Lastly, we find that the improvement of performance with alternative measures is mostly due to the underdiversification of investors. Actually, portfolios created based on a random process outperform the ones of investors, even with the alternative measures.

Our last chapter contributes to the knowledge regarding repurchase behavior by individual investors. This topic is not much documented, compared to buy and sale behavior. We follow previous works (Strahilevitz, Odean, and Barber, 2011) and evidence two patterns of repurchase. First, individual investors prefer to repurchase stocks that have been sold for a profit. Second, they prefer to repurchase stocks whose price has declined since the sale. Our first contribution is to evidence the repurchase patterns at the individual level, which enables to take into consideration the cross-section in these behaviors. Based on survival analysis, our second contribution is to examine the role of individual sophistication on the repurchase patterns. As in the first chapter, sophisticated investors are identified through the diversification level, trading of foreign assets, and the fact that they trade on multiple accounts. We show that sophisticated investors suffer less from these repurchase preferences. The documented patterns do not result from informational advantages. Indeed, investors who exhibit the repurchase behaviors do not earn higher returns on their repurchases than on their purchases and sales. In addition, these investors do not outperform their peers. Finally, we show that investors do not exhibit the repurchase biases due to a contrarian strategy. Consistently with previous conclusions, we support the hypothesis that the documented preferences are the result of investors emotional reaction to trading. More precisely, investors tend to avoid experimented and anticipated regret.

I briefly conclude by discussing the directions I plan to take for my future research. The first point in my agenda is to pursue the study on the repurchase behavior of individual investors, applying a methodology borrowed from the Marketing literature. A parallel can be drawn between consumers and investors. I plan to evaluate the degree of investors' loyalty to stocks (repurchasing or holding the same stocks) with measures of consumers' loyalty to a brand. The second point in my agenda is to extend my research on the alternative performance measure designed to fit the Behavioral Portfolio Model. In this perspective, I intend to evaluate the performance of the Behavioral Portfolio Theory optimal portfolio.

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Conclusion (Version française)

Les contributions de cette thèse de doctorat sont d'ordre méthodologique et empirique.

Le premier chapitre est consacré à l'analyse des performances des investisseurs individuels français. Les performances des investisseurs individuels ont été examinées dans un certain nombre de pays (Barber et Odean (2000) ; Grinblatt et Keloharju (2000)), cependant aucune recherche dans ce domaine n'a été menée en France. La première contribution de ce chapitre est de pallier cette absence. Nous montrons que les investisseurs français, comme leurs homologues étrangers, affichent des performances brutes et nettes ajustées au risque négatives. De plus les stratégies des investisseurs sous-performent une stratégie passive. En effet, ils prennent des décisions sous-optimales, telles qu'acheter des titres qui sous-performent ceux qu'ils vendent. Ces résultats sont robustes quelle que soit la période considérée (la bulle internet, la période post-bulle internet et la période haussière de 2003-2006).

La seconde contribution de ce chapitre est d'évaluer si les investisseurs les plus sophistiqués sont plus performants que les investisseurs les moins sophistiqués. Les chercheurs ont montré que les caractéristiques individuelles des investisseurs telles que le Q.I., le genre, l'âge, ou la richesse peuvent expliquer les variations dans les performances, mais le rôle de la sophistication reste inexploré. Nous nous appuyons sur des résultats existants concernant les mesures de sophistication et considérons que les investisseurs sont sophistiqués si ils détiennent des portefeuilles diversifiés, si ils échangent des titres étrangers et si ils traitent sur plusieurs comptes. Le dernier indicateur repose sur une spécificité fiscale française. Les investisseurs traitant sur deux types de compte sont considérés comme sophistiqués parce qu'ils possèdent un compte titres traditionnel mais aussi un deuxième compte leur permettant, en particulier, de bénéficier d'exonérations d'impôts (*i.e.*, un PEA). Nous montrons que les investisseurs sophistiqués ne sur-performent pas leurs pairs.

Le second chapitre de cette thèse examine l'hétérogénéité des performances des investisseurs individuels. Contrairement aux analyses menées dans la littérature, nous ne cherchons pas à expliquer cette hétérogénéité par des variables observables telles que les caractéristiques socio-démographiques. En revanche, nous établissons un lien entre les performances et les niveaux d'aspirations latents des investisseurs. Dans ce chapitre, les aspirations sont évaluées selon la Théorie Comportementale du Portefeuille (Shefrin et Statman (1985)) dans laquelle les investisseurs considèrent leur portefeuille comme une pyramide d'actifs. Les actifs les moins risqués se situent dans les couches inférieures et les plus risqués dans les couches supérieures. Chaque couche est associée à un niveau d'aspiration, *i.e.*, un niveau de richesse que l'investisseur souhaite atteindre pour un but spécifique (retraite, vacances, etc.). Ainsi, selon Shefrin (2005), les investisseurs à très faibles niveaux d'aspiration optent pour des bons du trésor, les investisseurs ayant des aspirations intermédiaires choisissent des actions, tandis que les investisseurs ayant des niveaux d'aspirations élevés choisissent des *call options* en dehors de la monnaie et des tickets de loterie. Le classement des investisseurs sur la base du type d'instruments échangés fait émerger deux profils d'investisseurs. Les investisseurs ayant de faibles aspirations détiennent des portefeuilles plus diversifiés et moins risqués que les investisseurs ayant des niveaux d'aspirations élevés. Ces derniers échangent moins fréquemment que leurs pairs.

Nous contribuons à la recherche sur les facteurs explicatifs de la performance de portefeuille par une comparaison des rentabilités ajustées au risque des investisseurs qui ont de forts/faibles niveaux d'aspirations. Nous montrons que les investisseurs à fortes aspirations sous-performent leurs pairs tandis que les investisseurs qui ont de faibles aspirations sur-performent leurs pairs.

La prise en compte des variables standards de l'hétérogénéité des performances telles que les facteurs de risque, la diversification et le turnover n'affectent pas significativement nos résultats.

Dans le troisième chapitre de cette thèse nous analysons l'influence des mesures de performance choisies pour évaluer les choix d'investissements des investisseurs individuels. Des études similaires ont déjà été réalisées sur des fonds (Zakamouline (2011)), mais cette question n'a jamais été abordée pour les investisseurs individuels. En nous basant sur des arguments théoriques, nous montrons que les performances des investisseurs individuels ne sont pas mauvaises *per se*, mais sont conditionnées au choix de la mesure de performance (classiquement le ratio de Sharpe). En effet, les mesures traditionnelles souffrent de nombreux défauts lorsqu'il s'agit d'évaluer les performances des investisseurs individuels.

Afin de répondre aux limites du ratio de Sharpe nous choisissons cinq mesures alternatives de performance. Dans ces mesures, le risque correspond aux déviations négatives des rentabilités par rapport à une rentabilité cible (*i.e.*, le *downside risk*). De plus, les ratios alternatifs traduisent différentes hypothèses portant sur le comportement des agents : Aversion aux pertes, Utilité espérée, Théorie des Perspectives et Théorie Comportementale du Portefeuille.

Trois résultats principaux émergent. Premièrement, le choix de la mesure de performance influence le classement des investisseurs. En effet, les permutations des rangs des investisseurs, lorsque l'on passe de l'évaluation de leur performance par le ratio de Sharpe à l'évaluation par les mesures alternatives, sont significatives. Deuxièmement, si l'on compare la performance relative du portefeuille des investisseurs par rapport à l'indice de marché en utilisant les mesures alternatives plutôt que le ratio de Sharpe, les investisseurs individuels ne sont pas de mauvais gestionnaires. En effet, une proportion plus importante des investisseurs bat le marché, notamment avec la mesure basée sur la Théorie Comportementale du Portefeuille. Enfin, l'amélioration des performances avec les mesures alternatives résulte principalement de la sous-diversification des investisseurs. En fait, des portefeuilles sous-diversifiés dont les titres sont choisis de manière aléatoire sur-performent les investisseurs de notre échantillon. Ce résultat persiste lorsque l'évaluation est réalisée avec les mesures alternatives.

Le dernier chapitre de cette thèse étudie les comportements de rachats des investisseurs individuels. Ce sujet est peu documenté, comparé aux comportements d'achat et de vente. Nous mettons en évidence deux comportements. Premièrement, les investisseurs préfèrent les titres qu'ils ont vendu pour un profit. Deuxièmement, ils sont plus enclins à racheter les titres dont le prix a baissé depuis la vente. Alors que les études existantes établissent ces préférences au niveau agrégé (Strahilevitz, Odean, et Barber (2011)), notre première contribution est de mettre en évidence ces comportements de rachat au niveau individuel. Ce niveau d'analyse permet de prendre en considération les différences dans les comportements entre les investisseurs.

A partir d'analyses de survie, notre seconde contribution est d'examiner le rôle de la sophistication sur les comportements individuels de rachat. Tout comme dans le premier chapitre, les investisseurs sophistiqués sont identifiés sur la base de leur niveau de diversification, de l'échange de titres étrangers, et de l'échange sur plusieurs types de comptes. Les investisseurs plus sophistiqués sont moins sujets aux préférences que nous étudions.

Nous montrons également que les schémas de rachat documentés ne résultent pas d'avantages informationnels. En effet, les investisseurs qui présentent de tels comportements n'affichent pas de rentabilités plus importantes sur leurs rachats que sur leurs ventes ou leurs achats. En outre, ces investisseurs n'atteignent pas de meilleures performances que leurs pairs. Enfin, nous montrons que l'application d'une stratégie contrariante ne permet pas d'expliquer ces comportements de rachats.

Nous soutenons l'hypothèse selon laquelle les préférences de rachats résultent de réactions émotionnelles des investisseurs qui cherchent en particulier à éviter le regret dans leurs choix d'investissements.

Concernant mes projet de recherche, l'étude des comportements de rachat des investisseurs individuels mérite d'être approfondie par l'application d'une méthodologie empruntée au Marketing. En effet, un parallèle peut être fait entre les consommateurs et les investisseurs. Dans cette optique, j'ai pour objectif d'évaluer le degré de fidélité des investisseurs (qui rachètent ou conservent le même titre) avec des mesures de fidélité à une marque.

La recherche sur les mesures de performances alternatives qui sont cohérentes avec la Théorie Comportementale du Portefeuille est un second enjeu. Plus précisément, j'ai pour ambition d'évaluer les performances du portefeuille optimal de la Théorie Comportementale du Portefeuille.

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Appendix A

Database and subsamples

Table A.1
Sample and subsamples used in chapters

	Investors	Trades	Explanations
Initial database	84,500	8,072,016	
Chapter 1	56,723	7,911,046	We keep investors who realize an average of more than 2 trades per year between 1999 and 2006.
Chapter 2	26,166	4,481493	Among the 56,723 investors, we keep investors who trade on two kinds of accounts (a French PEA and a classic account). Trading on several accounts constitutes a sophistication variable in chapter 1 and 4. We focus on one category of investors to avoid mixing up several effects in our analysis.
Chapter 3	24,766	1,882,044	We keep investors who have their account open between 2003 and 2006. We focus on this period when a larger part of investors exhibit positive Sharpe ratios.
Chapter 4	34,129	6,885,276	We keep investors who repurchased at least once.

Appendix B

Complementary review of literature

B.1 Trading performance of individual investors

B.1.1 Trading frequency and transaction costs

A large body of empirical research indicates that individual investors trade actively, to their detriment. The first study providing evidence that trading activity results in a decrease of net returns is the one of Schlarbaum, Lewellen, and Lease (1978a). The authors analyze round-trip trades from 2,500 accounts at a U.S. broker between 1964 and 1970. They document that investors earn strong returns (5.5%) before fees, but transaction costs yield portfolio returns that are similar to those available from passive investment strategies. In a second study conducted on the same database, Schlarbaum, Lewellen, and Lease (1978b) show that portfolios net returns fail to match a passive market index. More recently, Barber and Odean (2000) analyze portfolio performance of 78,000 households between January 1991 and January 1997. Contrary to Schlarbaum, Lewellen, and Lease (1978a) and Schlarbaum, Lewellen, and Lease (1978b) who analyse accounts at a full service broker, Barber and Odean (2000) examine investors at a discount broker. Though all investors have an access to newspapers specialized in finance, discount brokerage ensures that the transactions have not been influenced by professional recommendations. In a first step, the authors sort investors in quintiles according to their trading frequency. In gross terms, the portfolio return earned by investors who trade most and least is equal. Yet, in net terms, most active investors earn an average annual return of 11.4%, compared to 18.2% for least active investors. In a second step, Barber and Odean (2000) show that investors in the whole database earn on average 16.4% (net) annualy. By investing in the market index (weighted average of Nyse, Nasdaq, Amex indexes), they could have earned a return of 17.9%. Therefore trading activity results in non-negligible losses for investors, a large part of the penalty being traced to transaction costs. On the Taiwanese market, Barber, Lee, Liu, and Odean (2013) evaluate the total amount of shortfalls at 32 Billion Dollars, which represents 2.2% of Taiwans gross domestic product, or 2.8% of the total amount of household income. Commissions and transaction taxes represent more than 60% of the losses. Odean (1999) show that investors also lose money on their trades before costs. The author examines the trading profitability of 10,000 investors at a U.S. brokerage over the period 1987-1993. On a 1-year horizon, Odean (1999) shows that the stocks sold underperform the stocks purchased by 3.3%, before considering transactions costs.

This result persists even when trades more likely to have been made for liquidity, rebalancing, or tax purposes are excluded from the analysis. Indeed, excluding these rational trades, the stocks bought underperform the stocks sold by more than 5% on several horizons.

A summary of articles dealing with overtrading by individual investors is presented in table B.1.

Table B.1
Trading frequency and transaction costs

References	Database	Results
Schlarbaum, Lewellen, and Lease (1978a) and Schlarbaum, Lewellen, and Lease (1978b)	2,500 investors (1964-1970)	Returns fail to match a passive index
Barber and Odean (2000)	78,000 households (1991-1997)	Underperformance relative to a passive strategy
Odean (1999)	10,000 investors (1987-1993)	Stocks purchased underperform stocks bought before transaction costs

It is clear that other determinants than transaction costs penalize performances. Investors preferences, which are translated into their trading choices can explain their underperformance.

B.1.2 Stocks selection and trading behavior

A number of studies confirm that investors make detrimental choices in their trades. Bauer, Cosemans, and Eichholtz (2009) analyze 9 million trades realized by investors at a discount broker in Netherland. Consistently with the global evidence reported in the literature, they find that investors exhibit negative returns. However, this result is mainly attributable to investors who hold derivative products in their portfolio. Actually, the latter underperform their peers by 3% on a monthly basis. Thus, investors who trade complex instruments suffer from substantial losses. On the Finnish market, Grinblatt and Keloharju (2000) show that domestic investors tend to follow a contrarian strategy (i.e., purchase of past losing stocks) which results in negative returns. By contrast, a momentum strategy (i.e., purchase of past winning stocks) results in positive returns. Grinblatt and Keloharju (2000) precise that the momentum strategy is mostly applied by foreign investors who are mainly professional traders such as mutual funds, hedge funds and investment banks.

The disposition effect (i.e, the preference for selling stocks that have increased in value since bought (winners) relative to stocks that have decreased in value since bought (losers) established by Shefrin and Statman (1985) is another counterproductive pattern of preferences. Odean (1998) finds that winners that are sold earn an average return 3.4% (on a 1 year horizon) higher than losers that are kept in portfolio.[1]

Yet, it is worth noting that some investors realize outperforming returns compared to a passive portfolio management. Barber and Odean (2000) report that 25% of households are able to beat the market after accounting for transaction costs, by more than six percent annually. Several attempts have been made to understand whether these successful investors hold private information, are particularly skillful or merely lucky. Coval, Hirshleifer, and Shumway (2005) explain that individual traders are better po-

[1]Linnainmaa (2010) shows that the disposition effect and contrarian trades can be explained in large part by investors use of limit order. Even if investors decide randomly what they buy and sell, investors reliance on limit orders creates the appearance that they follow specific trading rules.

sitioned to exploit a given informational advantage. They are less constrained than mutual funds to track a given benchmark or to hold a diversified portfolio. By contrast, individual investors tend to hold concentrated portfolios, which is suboptimal according to the standard theory.[2] This propensity to underdiversify yields a debate about whether investors have the ability to identify winning stocks. Ivkovic, Sialm, and Weisbenner (2009) compare the performance of concentrated portfolios (containing one or two stocks) with the performance of diversified portfolios (containing three or more stocks). The study is restrained on investors with substantial accounts, to ensure that underdiversification is not linked to wealth constraints. Ivkovic, Sialm, and Weisbenner (2009) show that the purchases made by concentrated households exceed the benchmark portfolios by 1.3% points for those with relatively large portfolios (i.e., at least $25,000) and by 2.2% points for those with large portfolios (i.e., at least $100,000). Though on average, the stocks bought by individual investors underperform the stocks they sell by a wide margin, the reverse is true for households with concentrated large portfolios. The performance of concentrated portfolios is stronger for investments in local stocks, stocks that are not included in the S&P 500 index, and stocks with less analyst coverage. These findings suggest that concentrated investors possess informational advantages. Goetzmann and Kumar (2008) corroborate these conclusions and show that, among most active investors, the least diversified obtain better returns than the most diversified. Along the same lines, researchers investigate whether individual investors possess an informational advantage about companies that are close to where they live or in their industry of employment.

[2]See Lease and Schlarbaum (1974); Blume and Friend (1975); Kelly (1995); Mitton and Vorkink (2007); Kumar (2007); Goetzmann and Kumar (2008).

Actually, individual investors have a tendency to overweight the stocks from local companies in their portfolio.[3] This preference raises two hypotheses: Investors over-invest in local stocks either because they are familiar to them, or because they are better informed about these companies. Ivkovic and Weisbenner (2005) report that investment in local stocks outperform non local ones by 3.2% per year on a one-year horizon. Moreover, a portfolio that takes a long position in local investments and a short position in nonlocal investments earn an average monthly (risk-adjusted) returns of 17 (9) basis points. As for concentrated portfolios, excess returns to investing locally are even larger among stocks not in the S&P 500 index. These results indicate that individual investors are able to exploit locally available information to earn excess returns. Massa and Simonov (2006) corroborate these conclusions on Swedish data. However, the works of Seasholes and Zhu (2010) contradict these findings. The authors find that the purchases of local stocks significantly underperform the sales of local stocks.

Finally, Barber and Odean (2000) show that individual investors exhibit an inclination towards small capitalizations and high beta stocks. These preferences serve individual investors well during the period of analysis (1991-1997). Indeed, small stocks outperform large stocks by 0.15% per month. Therefore individual investors choices in terms of assets and trading behavior can explain their performance.

These results are summarized in table B.2.

[3] Local companies for a given investor are those with headquarter at the distance of 250 miles from locality of the investor.

Table B.2
Stock selection and trading strategy

References	Data	Strategy	Results
Bauer, Cosemans, and Eichholtz (2009)	68,000 investors (2000-2006)	Trading of derivative instruments	Undeperformance relative to investors who do not trade complexe products
Barber and Odean (2000)	78,000 households (1991-1997)	Preference for small capitalization	Small stocks outperform large stocks during the period
Grinblatt and Keloharju (2000)	Finnish markets (1994-1996)	Contrarian trading	Negative average performance
Ivkovic, Sialm, and Weisbenner (2009)	78,000 investors (1991-1996)	Underdiversification (1 ou 2 stocks)	Concentrated portfolios outperform more diversified ones
Ivkovic and Weisbenner (2005)	78,000 investors (1991-1996)	Overweighting in local stocks	Investments in local stocks earn a return higher than investments in non local stocks

B.1.3 Investors characteristics and trading performance

Another stream of literature analyze whether portfolio performance can be traced to investors individual characteristics. Grinblatt and Keloharju (2009) show on Finnish data that the stocks purchased by high-IQ investors outperform the stock purchased by low-IQ investors. The annualized spread between a portfolio containing the stocks bought by high-IQ investors and a portfolio containing stocks bought by low-IQ investors is 11%. These results control for experience, wealth, age of investors and stock characteristics. These authors explain that high-IQ investors exhibit superior market timing, stock-picking skills, and trade execution. Nicolosi, Peng, and Zhu (2008) find that a portfolio that mimics the investing decisions taken by most experienced investors outperform a portfolio that mimics the decisions taken by least experienced investors by 3 basis points per day. Investors learn from their trading experience and consequently adjust their behavior. The authors evaluate investors experience though the total number of purchases realized, the total number of stocks traded and the number of elapsed months since account opening. Though Nicolosi, Peng, and Zhu (2008) examine U.S. investors, Seru, Shumway, and Stoffman (2010) corroborate those results on Finnish data. Concerning demographic variables, Korniotis and Kumar (2009a) analyze the relation between age and performance. They find that older investors (more than 70 years) earn about 3% lower risk-adjusted annual returns. Conclusions regarding wealth (measured by portfolio value) are less clear. Barber and Odean (2000) do not find any difference in performance between large and small portfolios. Yet, Chen, Kim, Nofsinger, and Rui (2007) find that richer investors exhibit lower returns. Laslty, Barber and Odean (2001) report that men trade more than women. As a result, the returns earned by men are lower than the returns earned by women.

These results are summarized in table B.3.

Table B.3
Investors caracteristics

References	Data	Caracteristics	Results
Grinblatt and Keloharju (2009)	Finnish investors (1995-2002)	IQ	Stocks purchased by high-IQ investors outperform stocks chosen by low-IQ investors
Nicolosi, Peng, and Zhu (2008)	78,000 investors (1991-1996)	Experience	Excess portfolio returns improve with account tenure
Korniotis and Kumar (2009a)	78,000 investors (1991-1996)	Age	Performances decline with age
Barber and Odean (2000)	78,000 investors (1991-1996)	Wealth	No difference in performance between large and small portfolios
Barber and Odean (2001)	78,000 investors (1991-1996)	Gender	Men trade more which results in lower performance than women ones

B.2 Investors' sophistication

B.2.1 Socio-demographic variables

Socio-demographic variables are good proxies for sophistication. Dhar and Zhu (2006) find that wealthiest investors and investors employed in professional occupation are less prone to the disposition effect.[4] Indeed, the disposition effect for such investors is 10% to 20% less than that of their peers.

Along the same lines, Calvet, Campbell, and Sodini (2009) create a sophistication index composed of financial wealth, education level and family size of the investor. The authors show that an increase in this index has a negative impact on three types of investment mistakes: inertia in risk taking, underdiversification and the disposition effect.

Agnew (2006) reports that employed with the highest salary tend to make better choices regarding their 401(K) investments.[5] More precisely, the author examines three behavioral biases: Naive diversification strategy, investing in company stocks (familiarity bias) and opting not to participate in the company sponsored plan. Agnew (2006) evidences that participants who earn an average annual salary of $100,000 hold 12.7% less in company stocks, are 3% less likely to follow the naive heuristic and

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[4] More precisely concerning the variables, investors who earn less than $40,000 per year are sorted in the *low income* category, whereas investors who earn at least $100,000 are classified in the *high income* division. Concerning the occupation, individual are classified as working in professional occupations if they report working in professional/technical or managerial/administrative positions. Individuals are classified as working in non-professional occupations if they report working in white collar/clerical, blue collar/craftsman or service/sales.

[5] A 401(k) plan is the common name in the USA for the contribution pension account defined in subsection 401(k) of the Internal Revenue Taxation Code. Under the plan, retirement savings contributions are provided by an employer, deducted from the employee's salary before taxation (therefore tax-deferred until withdrawn during retirement)

37.7% more likely to participate in the plan than those earning less than $ 46,000 per year. Concerning the participation bias, Agnew (2006) explains that choosing not to participate in a 401(K) plan "*is the most obvious error an individual can make*" (p.958).

In the context of the choice of mutual funds, Bailey, Kumar, and Ng (2011) provide similar conclusions. The authors show that higher income, older, and more experienced investors make good use of mutual funds, holding a high proportion of fund for long periods, avoiding high expense funds, and experiencing relatively good performance. By contrast, less sophisticated investors select mutual funds for the wrong reasons. When they do buy mutual funds, they trade them frequently, tend to time their buys and sells badly, and prefer high expense funds and active funds rather than index funds. These investors are identified through their preference for lottery-like assets, their tendency to suffer from the disposition effect and their level of overconfidence

Age is also a reliable indicator for sophistication. Indeed, older investors hold less risky portfolios, and trade less frequently than younger ones. Yet, their skill deteriorate sharply around the age of 70 (Korniotis and Kumar, 2009a).[6]

Finally, Goetzmann and Kumar (2008) show that diversification level increases with age, income, wealth and education.

Unlike the previous results, Chen, Hong, and Stein (2002) do not find that middle-

[6]Feng and Seasholes (2005) assume that investors between 25 and 35 years are the most sophisticated. This age bracket is contradictory with Korniotis and Kumar (2009a) observations who report that sophistication increases with age (until 70). Feng and Seasholes (2005) point out that the economic system changed dramatically in China. Hence, younger investors who were educated in an open economy are more sophisticated than investors who grew up during times of highly centralized planning.

aged, active, wealthier investors and those from cosmopolitan cities make less cognitive errors.

B.2.2 Cognitive capacities

The degree of cognitive capacities is also used to detect sophisticated investors. In order to measure cognitive capacities, Christelis, Jappelli, and Padula (2010) refer to the "Survey of Health, Aging and Retirement in Europe" (SHARE) which surveys people aged 50 and above in 11 European countries. The survey covers a wide range of topics, such as physical health, socioeconomic status, financial transfers, and intensity of social interaction. A questionnaire to measure cognitive capacities of respondents is included, notably to evaluate their ability to perform numerical operations (i.e, numeracy), planning and executive function (i.e., fluency), and memory. Based on those two sources of data, Christelis, Jappelli, and Padula (2010) show that age and education, which are usual metrics for sophistication, are positively correlated with cognitive capacities. Along the same lines, Cagney and Lauderdale (2002) and Holtzman, Rebok, Saczynski, Kouzis, Doyle, and Eaton (2004) find that age, place of living and size of social network are correlated as well with intelligence.

Financial products do not all require the same degree of sophistication. Indeed, saving accounts require a lesser understanding of financial markets than stocks. Portfolio management requires an important investment in terms of time and efforts. This cost is necessary to get familiar with notions of transaction costs, returns, volatility and covariance, but constitutes a barrier for entering the stock markets. Christelis, Jappelli, and Padula (2010) evidence that cognitive disorder results in a lower propensity to hold stocks. This observation suggests that low cognitive abilities are likely to raise the costs to enter the market.

With measures built on the basis of "SHARE", Korniotis and Kumar (2013) distinguish "Dumb" investors from "Smart" investors. "Smart" investors trade more, hold more concentrated portfolios and favor local stocks. Despite their tendancy to suffer from these three behavioral biases, they exhibit a better performance on average. By contrast, "Dumb" investors underperform the benchmark. A large part of this difference can be explained by superior skills to select stocks. "Smart" investors tilt their portfolio toward stocks that have greater information asymmetry, are harder to value, and have low average performance. Hence, the portfolio distortions of "Smart" investors reflect an informational advantage.
Intelligence is also measured by the Intellectual Quotient. To estimate whether I.Q. accounts for differences in trading behaviors and conveys an advantage in financial markets, Grinblatt, Keloharju, and Linnainmaa (2011) analyze I.Q. scores from inductees in Finlands mandatory military service matched with trading data. The authors show that investors who have a higher I.Q. are less subject to the disposition effect, are more likely to engage in tax-loss selling, and are more likely to sell (hold) a stock at a 30-day high (low). Moreover, they find that high I.Q. investors also exhibit superior market timing skills, stock-picking skills, and trade execution. Grinblatt, Ikaheimo, Keloharju, and Knupfer (2013) complete these results in the context of mutual funds choices and show that high-I.Q. investors tend to avoid high-fee funds.

B.2.3 Direct measures of sophistication: the variables

Although the demographic variables are most commonly employed, some studies are based on direct variables to measure sophistication. For instance, Goetzmann and Kumar (2008) identify an investor as sophisticated if he short-sells and if he trades options. The relevance of these two measures is evidenced by Korniotis and Kumar (2013) who show that "Smart" investors (with high cognitive capacities) are more prone to invest in foreign stocks and in options. They also tend to short-sell. Along the same lines, Bailey, Kumar, and Ng (2011) show that investors who short sell choose their mutual funds more effectively. Finally, Kimball and Shumway (2010) find that more sophisticated investors (identified through a questionnaire) avoid investing in their own employee's stocks, diversify their portfolio and hold foreign stocks.

Feng and Seasholes (2005) consider that an investor is sophisticated if he tends to diversify his portfolios right from the start of his trading life. More precisely, an investor is sophisticated when he purchases more than one stock at the beginning of his investing career. The authors also use the total number of rights authorized for each account as a proxy for investor sophistication.[7] They assume that sophisticated investors are generally inclined to use more methods to trade. They apply for, and are granted, more rights at the time they open their accounts. Based on these indicators, Feng and Seasholes (2005) evidence that sophisticated investors suffer less from the disposition effect. Indeed, they exhibit a reduced sensitivity to losses of at least 67%.

[7] This is specific to the PRC, where the investor must apply for the right to trade and receive authorization for each method before he is allowed to use it

B.2.4 Direct measures of sophistication: the surveys

Surveys can be conducted to evaluate the knowledge and skill of individuals in finance (Van Rooij, Lusardi, and Alessie, 2011; Kimball and Shumway, 2010).
For instance, Van Rooij, Lusardi, and Alessie (2011) designed questions to measure basic financial literacy (numeracy and basic knowledge related to the working of inflation and interest rates) as well as questions to measure more advanced financial knowledge related to financial market instruments (stocks, bonds, and mutual funds). The answers to that questionnaire are matched with the 2005 DNB Household Survey which covers information about demographic and economic characteristics, focusing on wealth and saving data. The dataset contains over 2,000 households of the Dutch population. Among the findings of Van Rooij, Lusardi, and Alessie (2011), we can list that basic financial literacy increases with the education level. Moreover, advanced literacy is low among the young, is highest among middle-age respondents (particularly 40 to 60), and declines slightly at an advanced age (61 or older). The last observation is consistent with the result of Korniotis and Kumar (2009a). A large percentage of women display low literacy: 34.5% of women are in the first and lowest quartile of the literacy distribution while only 12.1% are at the fourth quartile; the corresponding figures for men are 15.9% and 37.2% respectively.

A summary of sophistication measures is presented in table B.4.

Table B.4
Measures of sophistication

Sort of measure	Variables	Authors
Socio-demographic	Age - Income - Wealth (Portfolio value) - Social network - Place of living	Korniotis and Kumar (2009a); Calvet, Campbell, and Sodini (2009); Dhar and Zhu (2006); Agnew (2006); Bailey, Kumar, and Ng (2011)
Cognitive capacities	IQ - Questionnaire evaluating executive functions, numeracy and memory	Grinblatt, Keloharju, and Linnainmaa (2011); Christelis, Jappelli, and Padula (2010); Korniotis and Kumar (2013); Frederick (2005)
Direct	Diversification - Trading of foreig stocks - Short selling - Option trading - Experience	Feng and Seasholes (2005); Goetzmann and Kumar (2008); Seru, Shumway, and Stoffman (2010)
Surveys	Basic questions in finance: Interest rates, inflation, instruments - Test on understanding of risk and return concepts - Notions regarding diversification	Van Rooij, Lusardi, and Alessie (2011); Kimball and Shumway (2010)

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Approches comportementales de la gestion individuelle de portefeuille

Résumé :

Cette thèse est composée de quatre chapitres qui contribuent à une meilleure connaissance des comportements d'échange des investisseurs individuels et de leur performance. Dans le premier chapitre, nous réalisons la première étude consacrée aux performances de portefeuille des investisseurs individuels français. A partir d'une base de données de plus de 8 millions de transactions réalisées par 56 723 investisseurs, nous montrons que les investisseurs français affichent des rentabilités ajustées au risque négatives sur leurs portefeuilles et font des choix d'investissement pénalisants. De plus, nous mettons en évidence que les investisseurs les plus sophistiqués ne sont pas plus performants que leurs pairs.

Dans le second chapitre, nous montrons que l'aspiration individuelle constitue un déterminant clé pour expliquer l'hétérogénéité des performances de portefeuille. Nous définissons les aspirations selon la Théorie Comportementale du Portefeuille. Les investisseurs qui ont de fortes aspirations détiennent des portefeuilles plus risqués, échangent plus fréquemment et diversifient moins que les investisseurs ayant de faibles aspirations. En contrôlant de la fréquence des échanges, de la diversification et des facteurs de risque habituels, nous montrons que les investisseurs ayant de fortes aspirations sous-performent les investisseurs ayant de faibles aspirations.

Dans le troisième chapitre nous analysons les performances des investisseurs individuels via des mesures adaptées à leurs préférences. Lorsque leurs performances sont évaluées avec ces mesures plutôt qu'avec le ratio de Sharpe, une plus grande part des investisseurs bat l'indice de marché. Cette observation jette un regard nouveau sur les capacités de gestion des investisseurs individuels. Cependant, nous montrons que l'amélioration des performances est liée à la skewness des portefeuilles plutôt qu'à une sélection de titres pertinente.

Dans le dernier chapitre, nous explorons les comportements de rachat des investisseurs individuels. Nous montrons que les investisseurs préfèrent racheter (1) les titres pour lesquels ils ont réalisé une plus-value lors de la vente (2) les titres dont le prix a diminué depuis la vente. Nos tests excluent les explications rationnelles et confirment que l'évitement du regret est à l'origine de tels comportements. Sur la base d'une analyse de survie, nous montrons que les investisseurs sophistiqués sont moins sujets à ces préférences.

Mots-clés : Investisseurs Individuels, Performance de Portefeuille, Comportements d'Echange

Résumé en anglais :

This dissertation is composed of four chapters that make a substantial contribution to existing knowledge of the trading behavior and performance of individual investors. The first chapter provides the most extensive study of the trading performance of French individual investors to date. Based on a large database of nearly 8 million trades realized by 56,723 investors, we show that French investors exhibit negative risk-adjusted returns on their portfolios, and make penalizing choices in their trades. We find that more sophisticated investors do not perform better than their peers, and we conclude that investors would gain more from applying a passive strategy.

In the second chapter, we evidence that individual aspiration is a key determinant of existing heterogeneity in portfolio performance. We define aspirations according to the Behavioral Portfolio Theory. Investors who have high aspirations hold riskier portfolios, trade more frequently and diversify less than investors who have low aspirations. After controlling for turnover, diversification and usual risk factors, we find that investors with high aspirations underperform investors with low aspirations.

In the third chapter we highlight alternative measures of performance that efficiently convey the real preferences of investors. When they are evaluated with these alternative measures rather than with the Sharpe ratio, a higher proportion of investors beat the market index. This observation challenges the global evidence that individual investors are poor portfolio managers. However, our evidence suggests that the improvement of an investor's performance is linked to portfolio skewness rather than relevant stock selection.

In the last chapter, we explore the repurchase behavior of individual investors. We find that French investors prefer to repurchase (1) stocks that have been sold for a gain and (2) stocks that have lost value since their sale. Our tests exclude rational explanations for these preferences and confirm our hypothesis that such patterns can be traced to the avoidance of regret in trades. We use survival analysis to demonstrate that sophisticated investors suffer less from the repurchase preferences.

Key words: Individual Investors, Trading Performance, Trading Behavior