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ESSAYS ON EXCHANGE TRADED FUNDS AND RETAIL INVESTORS

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STATISTICS
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LIDAM & Louvain Finance

DOCTORAL THESIS

**ESSAYS ON EXCHANGE TRADED FUNDS
AND RETAIL INVESTORS**

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Abstract

We live in an ever-evolving world and financial markets are certainly no exception to the rule. Fierce competition between market agents at different levels constantly lead to the creation of new financial instruments and products, promoted by the adoption of new technological advances.

Exchange traded funds (ETFs) have been one of the most innovative instruments in the past forty years, and this doctoral dissertation contributes to the financial literature by enhancing the understanding of several dimensions of ETFs, focusing on their use by individual retail investors in particular.

This dissertation consists of five chapters, including three essays in Chapters 2 to 4, each filling in some gaps in the literature on passive Exchange Traded Funds (P-ETFs) and retail investors. The first essay examines the characteristics of passive ETF users through an expanded profiling approach based on both trading records and survey-based data. The second essay investigates the trading behavior of passive ETF retail investors by using random matching procedure. The third essay highlights the performance of retail investors when they hold passive ETFs in addition to individual stocks.

The first essay shows that retail investors who trade passive ETFs are more sophisticated than those who do not. Investing in P-ETFs is driven by higher education, experience, financial literacy and longer investment horizon. Also, passive ETF retail investors are less overconfident, suffer less from local bias, and hold lower number of stocks relative to non P-ETF investors.

The second essay shows that when controlling for investors' attributes, P-ETF retail investors show different trading behavior than individual stock investors. They have better understanding of diversification, have a larger portfolio size, lower turnover, hold their assets for longer periods of time and are less willing to trade lottery-like stocks.

The third essay shows that heavy P-ETFs users invest more passively. The portfolio total and systematic risks are lower for passive ETF investors, while risk-adjusted performance is negative but still higher than investors who trade individual stocks only.

The three essays together suggest that passive ETFs are still not the most straightforward investment choice for retail investors. Even if they benefit from holding passive ETFs in their portfolio regarding their investment behaviors for example, they are still unable to fully grasp the potential of this financial instrument.

Research accomplishments

Research visit - Queen Mary University of London - School of Business and Management (Sep. – Dec. 2021, London, UK)

Working papers

- D'Hondt, C., Elhichou Elmaya, Y., Petitjean, M. (2020). What drives retail investment in passive exchange traded funds, *working paper* available at SSRN: <https://ssrn.com/asbtract=3522963>
- D'Hondt, C., Elhichou Elmaya, Y., Petitjean, M. (2021). Trading behavior of passive ETF retail investors, *working paper* available at SSRN: <https://ssrn.com/asbtract=3783738>
- D'Hondt, C., Elhichou Elmaya, Y., Petitjean, M. (2022). Do stock retail investors show better portfolio performance when they hold passive ETFs ? , *working paper* available at SSRN: <https://ssrn.com/asbtract=4145537>

Communications

- 38th AFFI conference (Saint Malo, FR, 2022)
- LFIN internal seminar (Mons, BE, 2022)
- 37th AFFI conference (Online, 2021)
- European Financial Management Association 2021 Annual meeting (Online, 2021)
- 6th international symposium in computational economics and finance (Online, 2020)
- 13th RGS Doctoral Conference in Economics (Dortmund, GR, 2020)
- LFIN internal seminar (Mons, BE, 2020)
- LFIN internal seminar (Mons, BE, 2019)

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My life as a doctoral student has come to an end and I am now starting a new one as as a father. When I look at my daughter Oulfa, I now know what truly matters in life.

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Chapter 1

General Introduction

"They say that as a customer you can only get two of these three things: fast/good/cheap. If it's fast and good, it isn't cheap. If it is good and cheap, it isn't fast. And if it's cheap and fast, well, it probably isn't that good. Turns out, I have found two things that prove this wrong: Vietnamese restaurants and exchange-traded funds (ETFs). Those are two times when fast, good, and cheap all tend to exist in wonderful harmony." (Balchunas, 2016)

With the globalization and sophistication of financial markets, characterized by impressive developments in technology, market infrastructure and high frequency trading, investors have been increasingly confused. The emergence of new financial instruments and the broader scope of "asset classes" put investors in delicate situations when they have to make optimal choices for their portfolios.

In the 1990s, the U.S and Canadian exchanges witnessed the arrival of a new financial vehicle known as Exchange Traded Funds (ETFs), and considered by Deville (2008) as one of the most spectacular success in financial innovation since the advent of financial futures. Fundamentally, ETFs are hybrid investment products, with features of mutual

funds combined to features of common stocks.¹ ETFs are like Index Funds since they aim at replicating the performance of a given benchmark as closely as possible, and like stocks, ETFs are listed on a exchange and can be traded intra-daily (Abner, 2016). By the end of 2021, the number of global ETFs hited 8,500 and the assets under management (AUM) reached US\$ 10 Tn compared to US\$ 0.58 Tn only in 2006, according to industry data provider ETFGI².

The ETF phenomenon is perhaps most revolutionary from the perspective of individual investors (Ferri, 2009). The expansion of this financial investing instrument, among both the so-called "smart money" (institutional investors, i.e., experts) and the so-called "dumb money" (retail investors) is due to many benefits such as low cost and fees, tax efficiency and fairness, transparency and diversification. ETFs appear as democratic instruments since they give retail investors access to many different investments areas and fields (including less liquid assets). For the first time ever in the history of investing, institutional investors and retail retail investors are using the same investment products and paying the same expense ratios (Balchunas, 2016).

Furthermore, the continuous technological evolution of e-commerce and financial applications in the last two decades, has greatly facilitate the access to stock market trading services. Hence, online trading has now become the prevalent form of stock market trading (Adamopoulos, 2014). Therefore there is a real need to expand investigations over the behavior of retail investors as they become "players" of their own financial investments strategies (Volpe et al., 2002).

Since the emergence of behavioral finance, notable progress has been made to give retail investors the attention they deserve, by challenging the fundamental assumptions of

¹The first ETFs created were passive with a multiplier equals 1, and their inception intend to provide access to passive investing and indexed funds to individual investors. Nowadays, there are a multiplicity of ETF types, such as active, leveraged, inverse or inverse-leverage with multiplier different from 1.

²<http://etfgi.com/index/home>

traditional finance and the Efficient Market Hypothesis (EMH), by including findings from other social sciences, especially psychology and sociology, into financial theories (Glaser et al., 2004).

This thesis is comprised of three essays that focus on three topics related to passive Exchange Traded Funds and retail investors. The three essays are interlinked based on the subject of the study. However, they are each independently presented and each chapter is made of individual sections dedicated to introduction, literature review and hypothesis, data and sample, results and conclusion.

This dissertation is structured as follows. In this introductory chapter, we outline our motivations, then present an overview of the behavior of retail investors. We then exhibit a summary of the three chapters that compose this study. We further present the three essays in Chapters II, III and IV. Finally, Chapter V is dedicated to a general conclusion.

1.1 Motivations to explore retail investors and ETFs

The 2017 Nobel prize winner in economics, Richard Thaler, is the last consecration in behavioral economics, but not the first in the field.³ Indeed, the Nobel prize committee explained that Thaler's work on adding new perspectives from psychology into economics had inspired many other researchers and transformed behavioural economics from being "a fringe and controversial" field to a "mainstream area" according to the Financial Times.⁴ Finance is witnessing a paradigm shift, from a neoclassical based framework to a psychologically based framework. Shefrin (2010) qualified this major change in the research stream by "behavioralizing" finance, which is according to the author the

³H.Simon (1978) and D.Kahneman (2002) two winners of Nobel prize, where their works are a pioneers to analyse the psychology of the decision makers.

⁴<https://www.ft.com/content/49f68431-8675-3a0c-ab51-b90c230ed2ba>

process of replacing neoclassical assumptions with behavioral counterparts. Also, he concludes that the future of finance will combine realistic assumptions from behavioral finance and rigorous analysis from neoclassical finance.

In this respect, several reasons can explain our motivations, for the present doctoral dissertation.

First, ETFs is relatively new innovative financial vehicles that are gaining more and more the ground among different market participants, and have become one of the fastest-growing segments of the investment management business in the last 25 years (Hill et al., 2015). The rise of ETFs and the expansion of their use, is a direct consequence of the multiple benefits that this financial vehicle may offer to its users such as simple access, transparency, liquidity, price discovery, tax efficiency and fairness among others.⁵

Second, investing with ETFs may be considered as the best possible manner to implement the principles of modern portfolio theory. Indeed, the heart basic principles of financial management implies a simple investment strategy based on well-diversified, low expense funds and minimal portfolio re-balancing (Bailey et al., 2011). ETFs and Index funds with low fees and low turnover, are cheap, convenient vehicles for retail investors. Moreover, ETFs are encouraging a new approach to investing that focuses on macroeconomic and thematic developments rather than single-stock investing. Moreover, many

⁵Investing in ETFs offers investors many benefits. Firstly, it offers diversification since ETFs cover all asset classes (stocks, bonds, commodities, foreign exchange, real estate) in all major countries and in all major currencies, thereby giving the possibility for investors to diversify their portfolios in terms of asset classes, assets, locations and currencies. Secondly, ETFs can be purchased at a low cost in comparison to the underlying assets they represent (Gastineau, 2001). For example, as pointed out by Kopcke et al. (2009), ETFs offer lower fees and lower total expense ratios in comparison to traditional mutual funds. Thirdly, ETFs are almost always more tax efficient than mutual funds (e.g., Poterba and Shoven (2002), Masterson and Wilchusky (2009), Moussawi et al. (2022)). This is due to the way ETF shares are created and redeemed, which occurs at the fund level in the primary market, granting ETF providers with means to lower their capital gain realizations relative to mutual funds. Fourthly, ETFs offer high transparency. While holdings in traditional mutual funds are usually revealed with a lag and only periodically throughout the year, every investor can know what lies inside an ETF since the holdings are disclosed on a daily basis. Finally, ETFs are user-friendly since they can be purchased or sold any time during the trading day, just like the most liquid stocks. The general high level of liquidity associated with ETFs offers investors a greater flexibility.

others investing strategies can be implemented with ETFs for both short- and long-term investment horizons.

Third, the study of the behavior of retail investors is an crucial subject in Behavioral Finance. Indeed, retail investors have gained interest as their study might explain many situations considered as "weird" or are still "puzzles" for the traditional financial theory (Barberis and Thaler, 2003; De Bondt et al., 2008). Retail investors have, for a long time, been excluded from a deep investigation or "under-studied" by academics because they were only considered only as "noise traders" (Black, 1986; De Long et al., 1990) . So, our research project has the ambition of participating in a deeper understanding of retail investors' approach towards ETFs, and to investigate broadly this new perspective, since it has never done before as best of our knowledge.

Finally, the tremendous and continuing growth of new information and communication technologies plays a very important role in the enlargement of online trading for all market participants, and especially among the retail investors. As such, the possibility for retail investors to access every financial market around the world, all asset classes and all financial instruments is now just few clicks away, and retail investors are on their own. Consequently, this situation will lead, without doubt, to the emergence of new biases and irrational behaviors. So, our goal as scientific researchers is to understand these biases, to find the reasons behind them and to try to find solutions to improve the welfare of investors and the society globally. In this respect, Kliger et al. (2014) in their survey over research in behavioral finance, report that among the current scientific community there is a strong preference for further research on individuals over research on groups and organisations.

1.2 Retail investors behavior

"The rise of behavioral economics is sometimes characterized as a kind of paradigm-shifting revolution within economics, but I think that is a misreading of the history of economic thought. It would be more accurate to say that the methodology of behavioral economics returns economic thinking to the way it began, with Adam Smith, and continued through the time of Irving Fisher and John Maynard Keynes in the 1930s"(Thaler, 2016)

Since the works of Allais (1953), Simon (1956) and Tversky and Kahneman (1974) regarding judgments and decision making of people with limited cognitive resources, academics and scientific researchers have kept the assumptions of traditional finance theory under scrutiny. Indeed, several studies investigated the validity of the axioms of traditional finance using distinct experiments, approaches and methodologies, where the major finding is that retail investors deviate from the assumption of perfect rational behavior (Subrahmanyam, 2008).

Nowadays, there is an abundance of papers in the financial literature that document the presence of various biases in the behavior of retail investors (Beshears et al., 2018). The literature point out also variation of behaviors and outcomes among individuals, which may be explained by some of their characteristics and attributes, as for example gender, age, level of education, income, financial literacy etc. In this section, we discuss four biases among the main puzzles linked to investing decisions of retail investors: overconfidence, under-diversification, poor investing performance and disposition effect.⁶

⁶The financial literature identified several others behavioral biases, as for example mental accounting (Thaler, 1985), familiarity bias (Huberman (2001) and Grinblatt and Keloharju (2001a)), home and local bias, confirmation bias, Narrow framing, herding effect etc. (Kumar and Goyal (2015), Huang et al. (2016) and Zahera and Bansal (2018))

According to Fabre and François-Heude (2009) overconfidence can be defined as "*the tendency to overestimate the probability of achieving one's objectives as a result of a presumptuous belief in one's abilities or attributes as they may be used to bring about a particular outcome*". The literature suggests that overconfidence happens when investors overestimate their predictive skills and the precision of information or underestimate the impact of chance and the volatility of random events in financial markets (Glaser and Weber, 2007; Jain et al., 2015). In the same vein, Guiso and Jappelli (2005) find that individuals are overconfident when they assess their own financial knowledge, and Xia et al. (2014) find that investors who tend to overestimate their financial knowledge participate more to financial markets than the ones who do not.

Several individual characteristics are identified to be positively related to overconfidence in the literature such as gender, education level and wealth. Barber and Odean (2001) find that men, who are on average more overconfident than women, trade more and have lower returns. Overconfident investors are more prone to make investment mistakes such as over-trading (Barber and Odean, 2000; Graham et al., 2009), which also leads to poor investment performance (Konana and Balasubramanian, 2005; Glaser et al., 2004).

Regarding under-diversification, despite the famous works of Markowitz who showed that diversification is the only free lunch in investing, a long series of papers showed that retail investors do not diversify their portfolios appropriately (Blume and Friend, 1975; Kelly, 1995; Barber and Odean, 2000; Goetzmann and Kumar, 2008). And even when retail investors decide to hold stocks, their selection is generally sub-optimal. Indeed, retail investors exhibit familiarity bias, as higher proportion of their holdings are stocks of their own employer (Benartzi, 2001; Mitchell and Utkus, 2002; Poterba, 2003), stocks of companies headquartered in their own country (French and Poterba, 1991; Cooper and Kaplanis, 1994; Tesar and Werner, 1995), stocks of domestic companies headquartered closer to their home (Grinblatt and Keloharju, 2001; Huberman, 2001; Ivković and

Weisbenner, 2005) and tend to favorite stocks listed in countries that share a common language, what is named the "language effect" (Chan et al., 2005; Ammer et al., 2012; Bellofatto, 2017).

As for the under-performance of retail investors, quite a few studies has found that retail investors on average underperform in stock market (Odean, 1999; Barber and Odean, 2000; Grinblatt and Keloharju, 2001; Barber and Odean, 2008; Choi et al., 2002). The literature provides several explanations for this outcome, for example Barber and Odean (2000) find that retail investors who trade more perform worse, and Barber and Odean (2001) show that overconfidence can explain high trading levels and the resulting poor portfolio performance, and men are on average more overconfident than women, trade more and have lower returns. Also Dorn and Sengmueller (2009) show that individuals who over trade, report also that they enjoy investing or gambling. Entrop et al. (2016) find that retail investors under-performance is related to the investors poor stock selection abilities. Retail investors' poor selection and bad timing had been also found when they choose to invest in ETFs (Bhattacharya et al., 2017).

Finally, an other main reason that explains the poor performance of retail investors is the disposition effect. The latter was initially introduced by Shefrin and Statman (1985), where the authors find that retail investors tend to sell winning stocks early to realize the gains and they tend to hold the losing stocks for long time so as to delay the losses. The disposition effect is one of the most deeply rooted biases in the literature, and several reasons are identified as source of the bias: the investors' unjustified belief in stock prices mean-reversion (Zuchel, 2001), the regret theory as investors' preference for self-esteem rather than for regret (Subrahmanyam, 2008), the Prospect Theory (Jain et al., 2015) and the Mental Accounting Theory (Thaler, 1985). Unexpectedly, Chang et al. (2016) find that there is a reverse disposition effect for actively managed mutual funds but not for the passively managed mutual funds.

1.3 A three-essay doctoral research

In this section we present the three papers that constitute the present doctoral dissertation. The goal of this Ph.D. thesis is to expand the financial literature linked to retail investors and Exchange Traded Funds in three different angles by addressing three interconnected questions, that could be summarized as follow: 1) Who are passive ETF users among retail investors ?, 2) How do retail investors use ETFs and 3) Do retail investors benefit from investing in passive ETFs besides their individual stocks holdings ?. Each of the three questions have been investigated in-depth in separate papers (chapters).⁷

1.3.1 Essay 1: What drives retail investment in passive Exchange Traded Funds?

In essay I, based on trading records and survey data, we investigate drivers of passive Exchange Traded Funds investing and determine very clear and complete profile of retail investors who hold passive Exchange Traded funds, using four sets of investors' attributes and characteristics: socio-demographics, objective variables, subjective variables and behavioral biases.

Opting for a zero-negative binomial models, our main findings show that the retail investors who are more likely to invest in P-ETFs are those who are better educated, self report both higher financial literacy and longer investment horizon, display longer trading experience, hold a better diversified stock portfolio, and trade stocks more intensively. However, retail investors with higher target return, who suffer from either overconfidence or local bias are less prone to invest in P-ETFs.

Our results show that retail investors P-ETFs trading activity is boosted by higher

⁷Three essays are joint work with Prof. Catherine D'Hondt and Prof. Mikael Petitjean

education, better financial literacy, longer investment horizons, lower target returns, and strong trading experience. Moreover, for P-ETFs retail investors we find a trade-off between the magnitude of their investments in P-ETFs and the magnitude of their investments in stocks, emphasizing the presence of a substitution effect between stocks and P-ETFs.

Despite that literature asserts that passive ETFs are the most suitable financial instrument for investors with limited resources, our results show that retail investors who trade P-ETFs are more sophisticated than those who do not.

1.3.2 Essay 2: Trading behavior of passive ETF retail investors

In essay II, we examine the passive ETFs retail investors' behavior by controlling for all of the key covariates related to sociodemographic attributes, trading activity, and subjective individual characteristics. We apply a random matching procedure to fine tune the comparison between the retail investors who hold P-ETFs and reference group of retail investors who hold individual stocks only.

Building on essay I, and after developing the profile of P-ETFs investors and answering the question of "Who ?", in this essay we extend the analysis over "How ?" and the way retail investors use passive ETFs to achieve their objectives. First, we investigate whether investors who hold P-ETFs manage their securities differently than those who invest in individual stocks only. Second, we test whether P-ETFs retail investors show safer attitude against trading lottery-like stocks.

Results show that retail investors who invest in P-ETFs trade their assets differently compared to those who hold individual stocks only. Indeed, their portfolio is better diversified as they include more securities, and they adopt a long-term perspective with

respect to portfolio turnover and asset holding period. Furthermore, retail investors who hold P-ETFs show conservative attitude regarding stock gambling, since they are less prone to trade lottery-like stocks.

Our results confirm that, P-ETFs retail investors display coherent trading behaviours, in line with the nature of this financial instrument.

1.3.3 Essay 3: Do stock retail investors show better portfolio performance when they hold passive ETFs ?

As a logical follow-up of essays I and II, in essay III we investigate the portfolio performance of retail investors who combine stocks and passive Exchange Traded Funds, and we test whether this performance is higher than a reference group of retail investors who invest exclusively in individual stocks.

In our analyses we use the propensity score matching to control for confounding factors and select the most suitable investors in reference group, and we take into consideration the observable weight of P-ETFs in the aggregate portfolio of the target group. Our investigation of portfolio performance is achieved through several risk-adjusted return measures at the aggregate level and for each security type separately, P-ETFs and stocks.

Our findings show that heavy P-ETF investors adopt more passive investing behaviour when managing their portfolio. In addition, only light P-ETF investors show significant higher portfolio performance, as measured by gross and net excess returns, than individual stock investors, while both (heavy and light) P-ETF investors exhibit lower total and systematic risks and higher risk-adjusted portfolio performance, as measured by alpha, Sharpe-ratio and Treynor ratio.

However, all risk-adjusted performance measures are negative, meaning that P-ETF

investors perform "less bad" than individual stock investors once their exposure to risk factors are accounted for. And being less bad is simply not good enough.

The last chapter of the dissertation is dedicated to a general conclusion, we present the implications as well as the limitations of our doctoral thesis and propose some different avenues for future research.

1.3.4 Database

In this doctoral thesis, we make use of a very interesting database coming from an online Belgian brokerage house and cover the trading records of 26,410 retail investors over the period January 2003-March 2012. In addition to detailed information about the retail investors' trading activity, a second dataset was provided to complement the first one with more qualitative information about the retail investors, regarding sociodemographics and survey-based data from MiFID questionnaires. The latter are known as the *Appropriateness* test, which is required before providing execution and transmission of orders on complex financial instruments, and the *Suitability* test, which is required before providing investment advice or portfolio management services. Both tests provide self-reported answers of retail investors and are therefore not affected by any conversation with a broker or a financial advisor. Figure 1.1 displays the three types of services recognized by the MiFID Directive, as well as information that investors need to provide accordingly.

The 26,410 investors constitute our full sample. However, depending on the different research questions of each chapter that constitutes this thesis, we use different subsamples. In Chapter II, we use the full sample as you can see in Section 2.3. Figure 1.2 displays the evolution of number of investors over 2003-2012 period.

You would normally go to a MiFID investment firm for one of the following reasons:

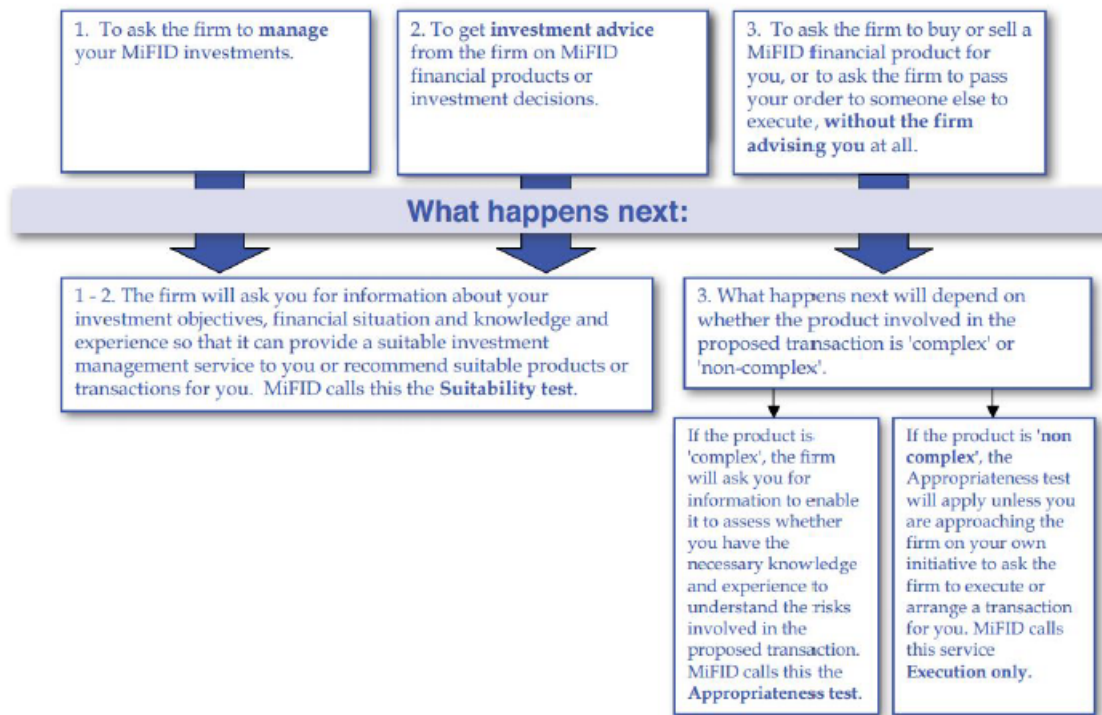


Figure 1.1: MiFID services.

This figure exhibits the three types of services recognized by the MiFID Directive, as well as information that investors need to provide accordingly. Source: CESR (2008).

In Chapter III, we use a subsample of 1,023 investors divided in two groups. The first is the Target Group (TG), which is composed of the 512 investors who invested in both individual stocks and P-ETFs. The second is the Reference Group (RG), which is composed of the remaining 511 investors who only invested in stocks. In Section 3.2 we explain that the goal is to test whether investors behaviours depend on the weight allocated to P-ETFs in their portfolios we create four sub-TGs (TG1, TG2, TG3 and TG4), in which we cluster TG investors according to the weight of P-ETFs in their aggregate portfolio. The goal is to identify 'light, medium and heavy users of P-ETFs' with a good number of observations (investors) in each sub group as shown in Figure 3.2.

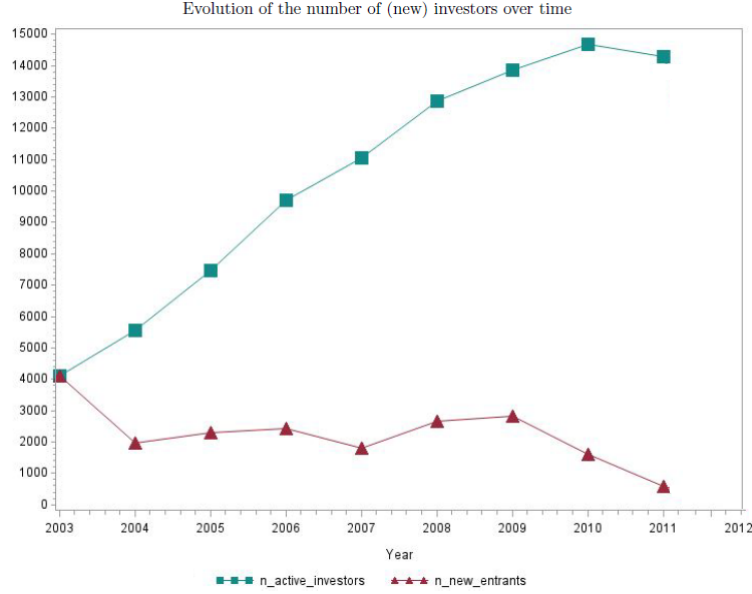


Figure 1.2: Evolution of the number of (new) investors over time.

This figure shows the evolution of the number investors over January 2008 to January 2012 period. The number of investors with at least one trade on stocks is increasing over time (green line). However, the number of new entrants is stable between 2004 and 2009 before starting to fall (red line).

In Chapter IV, we use a subsample of 907 over the January 2008-March 2012 period. Figure 4.1 displays the evolution of number of investors per month since January 2008. The decision to start our analysis from January 2008 is explained by the fact that the number of investors (observations) with passive ETFs in their portfolio was lower than 100. To better estimate the contribution of passive ETFs in the portfolio performance we kept the same categorization as in Chapter III, where the Target and the Reference groups are described in section 4.2.1. However, we further split the TG in two subgroups: ‘Light’ P-ETF users (LTG hereafter) and ‘heavy’ P-ETF users (HTG hereafter) instead of four sub-groups. HTG includes retail investors who invest at least 50% of the aggregate portfolio in P-EFTS, while the weight is less than 50% in LTG. The choice of two sub-TGs is made to keep a good number of observations (investors) in each sub group as shown in Figure 4.2.

Chapter 2

What drives retail investment in passive exchange-traded funds?

Chapter Abstract

We profile retail investors in passive exchange-traded funds (P-ETFs) using both trading records and survey-based data provided by a major brokerage firm for a very large pool of clients over nearly a decade. There is overall strong evidence that retail investors who trade P-ETFs are more sophisticated than those who do not. Both the probability and magnitude of retail P-ETF investing are driven by higher education and longer trading experience. Retail P-ETF investors self-report higher financial literacy, a longer investment horizon, and a lower target return. These investors are less overconfident, and their investment is less biased locally. The more active retail P-ETF users hold a lower number of stocks and modify the composition of their stock portfolio less extensively, pointing to a substitution effect between stocks and P-ETFs.

Keywords: Behavioral biases, Passive ETFs, Financial literacy, Retail investors.

JEL classification: G11, G40, G53

2.1 Introduction

Passive exchange-traded funds (P-ETFs) seek to mimic the performance of the stock market or a subset of it. They have become one of the most attractive innovations in finance, mostly because they are cheaper, less opaque, and more tax efficient when compared to active ETFs which have historically failed to outperform the benchmark net of fees. Passive ETFs have attracted nearly \$3 trillion in assets over the last 10 years, while active ETFs have drawn only \$200 billion. Even Warren Buffett, who is cited in Schroeder (2008), p. 685, strongly recommend P-ETFs to retail investors who have by definition limited resources, i.e. limited capital, time, or skills: ‘Stocks are the things to own over time. Productivity will increase and stocks will increase with it. There are only a few things you can do wrong. One is to buy or sell at the wrong time. Paying high fees is the other way to get killed. The best way to avoid both of these is to buy a low-cost index fund, and buy it over time. Be greedy when others are fearful, and fearful when others are greedy, but don’t think you can outsmart the market [...] Very few people should be active investors’.¹

Very little is known about the profile of retail investors who follow Warren Buffet’s advice and hold P-ETFs in their portfolio. To the best of our knowledge, the only major reference on the topic of P-ETF users is Bhattacharya et al. (2017), but they essentially focus on whether P-ETF retail investors display better performance. Compared to non-users, they find that P-ETF users do not improve their portfolio performance. Regarding the ETF users’ profile more specifically, they document that P-ETF users are younger, wealthier (in terms of both portfolio value and overall wealth), and have a shorter relationship with brokerage.²

¹Understanding what affects the performance of passive and active investment vehicles is critical for retail investors. Several studies shown the dominance of ETFs over mutual funds, as for example in Prather et al. (2009) who find that ETFs dominate mutual funds when total annual costs are taken into consideration. Farinella and Kubicki (2018) also find that passive ETFs have statistically higher annual returns and lower annual fees than mutual funds.

²Other studies consider the population of retail investors who hold a very heterogeneous set of products. For example, Davydov et al. (2017) consider retail investors who invest in exchange-traded products (ETPs) which include ETFs, ETCs (exchange-traded commodities), and ETNs (exchange-

As in Bhattacharya et al. (2017), Davydov et al. (2017), and Enete et al. (2018), we focus on individual investors who invest in passive ETFs during the sample period, that we call P-ETF users. Despite these primary findings, no previous study has relied on both trading and survey-based data to establish the drivers of P-ETF investing and determine more comprehensively the profile of retail investors who hold P-ETFs.³

Our data set includes the trading records of 26,140 retail investors at a major brokerage firm from January 2003 to March 2012. It also contains matched survey-based information collected within the framework of the MiFID regulation in place in the European Union member states since November 2007.⁴

Contrary to Bhattacharya et al. (2017), we therefore use both types of data, which leads us to include four sets of factors potentially driving retail ETF investing, namely, sociodemographics (such as gender, age, education, and language), subjective individual characteristics (such as target return, risk tolerance, and financial literacy), objective measures of trading activity (such as experience and stock portfolio size), and behavioural variables (such as proxies for overconfidence, lack of diversification, and local bias).⁵ We thereby minimize the risk of introducing an omission bias and are able to contrast what retail investors declare to what they actually do.

To further contribute to the literature, we opt for a zero-inflated negative binomial

traded notes). They provide evidence that younger investors may be relatively more skilful users of ETPs. They also find that ETP investors perform worse than those who invest in mutual funds. Enete et al. (2018) focus on ETF users only. They find that ETF users have more subjective financial knowledge than non-users. They nevertheless do not distinguish between passive and active ETFs, such as leveraged, inverse, or inverse leveraged ETFs. These active ETFs have a multiplier different from 1 and are not passive. D'Hondt et al. (2020) show that the typical user of leveraged ETPs looks like an overconfident gambler willing to take a high risk, while inverse leveraged ETPs are used by some highly loss averse investors for hedging purposes. In our study, we exclude them.

³To the best of our knowledge, D'Hondt et al. (2020) is the only study that also relies on both trading and survey-based data to sketch the profile of ETF users. However, this study focuses on the typical retail investor who trades leveraged ETPs.

⁴MiFID stands for the Markets in Financial Instruments Directive. MiFID I (2004/39/EC) is known as the first version of this Directive, while a review of it was implemented in January 2018 (known as MiFID II (2014/65/UE)). For more details on the MiFID regulation, please visit the European Commission website (https://ec.europa.eu/info/law/markets-financial-instruments-mifid-ii-directive-2014-65-eu_en).

⁵Behavioural variables are based on transaction records as in Bailey et al. (2011) who investigate the effect of behavioral biases on the mutual fund choices of US individual investors.

(ZINB) regression model. The benefit of using a ZINB model is twofold since it helps explain the *likelihood* of trading P-ETFs but also the *magnitude* of P-ETF trading. This approach allows us to go beyond what was done previously.

Our main findings may be summarized as follows. The retail investors who are more likely to invest in P-ETFs are those who are better educated, self-report both higher financial literacy and a longer investment horizon, exhibit longer trading experience, hold a better diversified stock portfolio, and trade stocks more intensively. In contrast, retail investors who declare a higher target return, who suffer more from either overconfidence or local bias, are less likely to invest in P-ETFs. When we only consider retail investors who use P-ETFs, we find that their trading activity in P-ETFs is boosted by higher education, better financial literacy, longer investment horizons, lower target returns, and stronger trading experience. The most active investors in P-ETFs are also older and less subject to local bias. Furthermore, there is a trade-off between the magnitude of their investments in P-ETFs and the magnitude of their investments in stocks. Investors who trade P-ETFs more actively hold a lower number of stocks in portfolios and modify the composition of their stock portfolios less extensively (i.e., have a lower turnover). This result points to a substitution effect between stocks and P-ETFs as trading in P-ETFs increases.

This paper contributes to the ongoing debate over passive retail investing by providing strong evidence that retail investors who trade P-ETFs are more sophisticated than those who do not.

The rest of the paper is organized as follows. Section 2.2 reviews the relevant literature and presents our five testable hypotheses regarding the drivers of retail investment in P-ETFs. Section 2.3 describes our data and provides statistics for our sample of investors. Our empirical results are reported in Section 2.4. Section 2.5 concludes.

2.2 Literature and hypotheses

The objective of this paper is to identify the profile of retail P-ETF investors, considering sociodemographics, individual characteristics, trading activity, and behavioural biases.⁶ A particularly interesting research question is whether P-ETF users differ in terms of financial literacy, financial experience, and behavioural biases. The reason why we focus on these three aspects is justified by the widely documented impact these factors have on both the investors' wealth and social welfare in general.

2.2.1 Financial sophistication and retail investment in P-ETFs

Financial sophistication of retail investors has been investigated in several papers in the literature (i.g., Calvet et al. (2009); Van Rooij et al. (2011a); Lusardi and Mitchell (2014); Lusardi et al. (2017); Lindblom et al. (2018); Titman et al. (2022)), where we find that it is composed of different investors' characteristics such as financial literacy, financial experience, higher education, financial situation and wealth, investment horizon, and portfolio diversification level.

Financial literacy refers to the ability to process economic information and make sound decisions about financial planning, wealth accumulation, debt, and pensions (Lusardi and Mitchell, 2014). There is ample evidence that financial literacy benefits investors. In summary, higher financial literacy is associated with better day-to-day financial management abilities (e.g., Hilgert et al. (2003)) and successful retirement planning (e.g., Lusardi and Mitchell (2007)). It also helps reduce the negative effect of behavioural biases on wealth (e.g., Baker and Nofsinger (2002)) and the probability of underdiversification (e.g., Gaudecker (2015)). Empirical evidence also shows that less literate investors exhibit lower portfolio performance (Gaudecker (2015), Bellofatto et al. (2018), Bianchi (2018)).

⁶A detailed description of our variables is provided in Section 2.3.2.

The level of financial literacy of retail investors may usually be evaluated in two ways. When based on a set of questions addressing the basics at the root of saving and investment decisions,⁷ measures of financial literacy are labelled as *objective* because actual knowledge is revealed through correct answers. By contrast, measures of *subjective* financial literacy rely on questions asking people to self-assess their financial knowledge and expertise. Although the correlation between objective and subjective literacy may not be taken for granted (Lusardi and Mitchell, 2014),⁸ prior research points to a positive relationship between subjective literacy and the actual level of knowledge (e.g., Dorn and Huberman (2005), Van Rooij et al. (2011b), Babiarz and Robb (2014)). According to Courchane and Zorn (2005), subjective financial literacy is one of the most significant factors in determining the way people invest. In the same vein, Bellofatto et al. (2018) find that investors with higher subjective financial literacy seem to invest in a smarter way, even after controlling for gender, age, portfolio value, trading experience and education. These investors are less prone to the disposition effect and display higher performance.

Of particular interest for our research question, financial literacy is also a robust driver of awareness about investment alternatives to stocks. Using survey data, Müller and Weber (2010) provide evidence that there is a positive relationship between financial literacy and the probability of investing passively. Bellofatto et al. (2018) show that investors who report higher financial literacy are more likely to invest in funds; i.e., they tend to concentrate their portfolios on a small set of stocks and achieve diversification through investment funds holding. Enete et al. (2018) find that ETF users have more subjective or objective financial knowledge than non-users of ETFs.

In addition to financial literacy, experience is another key element in the decision-making process of investing. For example, trading experience eliminates the reluctance of retail investors to realize losses (Feng and Seasholes, 2005) and positively influences overall

⁷These basics include topics, such as compounding, inflation, and diversification.

⁸There might be exceptions to the rule (e.g., Lusardi and Mitchell (2011)), but individual investors tend to have a relatively reliable perception of their knowledge.

investor behaviour (Lyons et al., 2006). Retail investors learn from their trading experience, as documented in Nicolosi et al. (2009) or Koestner et al. (2017).

Regarding investments in funds, Wang (2011) show that experience (in addition to knowledge and income) is an important factor impacting the way younger generations invest in mutual funds. Bailey et al. (2011) report that sophisticated investors, i.e., better informed, higher income, older, and more experienced investors, make good use of mutual funds. In particular, they hold a high proportion of funds for long periods of time, avoid high expense funds, and experience relatively good performance.

Level of portfolio diversification is another component of investor sophistication, since that underdiversification is well-documented investment mistake made by retail investors (Koestner et al., 2017). The majority of retail investors and households typically own only a few stocks in their portfolios (e.g., Kelly (1995); Polkovnichenko (2005)). For example, Kumar and Lee (2006) and Korniotis and Kumar (2013) document that a typical investor at a major U.S. discount brokerage house over the period 1991-1996 holds a four-stock portfolio (with a median of three). Consistently, Leal et al. (2017) report a three-stock portfolio for a typical investor at a Portuguese brokerage firm over the 2003-2007 period, and Bellofatto et al. (2018) find a four-stock portfolio for the median investor at a Belgian brokerage house over the 2003-2012 period. This lack of diversification negatively affects financial well-being in general (e.g., Barber and Odean (2000)) and depends on the degree of investor sophistication (e.g., Goetzmann and Kumar (2008)).

Although transaction costs have usually been mentioned as one of the major drivers of underdiversification (Evans and Archer, 1968), they are no longer relevant because of the emergence of ETFs and index funds, which have allowed for a drastic reduction in explicit transaction costs (Domian et al., 2007). P-ETF users are arguably expected to be more aware of diversification principles than non-users of P-ETFs since P-ETFs are *de facto* inexpensive diversification tools at the disposal of investors. Hence, the non-users of P-ETFs are expected to hold less diversified stock portfolios than P-ETF users. The same reasoning might also apply to the subsample of P-ETF users: among

P-ETF users, those whose stock portfolio is more underdiversified are expected to trade P-ETFs less extensively.

Based on the aforementioned findings, we formulate our first two hypotheses to be tested with the ZINB model in Section 2.4.

H1. The more financially sophisticated retail investors are, the more likely they are to invest in P-ETFs.

H1*. Among the users of P-ETFs, the more financially sophisticated users trade P-ETFs more often.

2.2.2 Behavioral biases and retail investment in P-ETFs

Behavioral biases lead to costly investment mistakes among retail investors (e.g., Singh (2010), Ramiah et al. (2015), Koestner et al. (2017)). It is well established in the literature that individuals generally suffer from overconfidence⁹ (e.g., Fischhoff (1982), Moore and Healy (2008), De Bondt and Thaler (1995), and Camerer and Lovo (1999)). The detrimental impact of overconfidence on trading behaviour and/or portfolio performance has been widely documented (among others, Barber and Odean (2000), Barber and Odean (2001), Dorn and Huberman (2005), Glaser and Weber (2009)). Overconfidence especially leads to overtrading (Odean, 1999) and riskier portfolios (Carpentier and Suret, 2011).

Considering mutual funds, Bailey et al. (2011) find that overconfident investors are more likely to select higher expense funds and avoid index funds. Moreover, when overconfident investors buy mutual funds, they trade them frequently and prefer active funds with high expense ratios rather than passive index funds with low expense ratios, such as ETFs. Consistent findings are reported in Davydov et al. (2017). Hence, we

⁹Overconfidence is observed when people's subjective confidence in their own ability is greater than their actual performance. In short, this concept is often related to (a) an overestimation of one's skills, (b) a belief that one is better than the median person (i.e., better-than-average effect), and (c) overprecision in one's beliefs (sometimes labelled miscalibration).

expect that P-ETFs are not targeted by overconfident investors.

Mental accounting is another behavioural concept developed by Thaler (1980) to describe the process by which the people keeps goals and moves towards those goals separately from each other. We follow Barberis and Huang (2001) who show that people engage in narrow framing by paying attention to narrowly defined gains and losses when they do their mental accounting. The reason for this mechanism according to Baker and Nofsinger (2002) is that this process helps people with their self-control, since that keeping things separately allows better measurement of the progress of each goal.

Narrow framing is a recognized behavioural bias among retail investors. This bias refers to their tendency to evaluate and select assets in isolation (Barberis et al., 2006). In other words, contrary to the assumptions of Markowitz’s portfolio choice theory, retail investors do not consider their portfolio as a whole. Kumar and Lim (2008) find that narrow framing is accentuated when portfolios contain a very low number of different stocks. Kumar (2009) report a positive relationship between uncertainty and narrow framing; i.e., investors are more likely to adopt focused and narrower decision frames in more uncertain environments. The degree of narrow framing is, however, negatively related to investor sophistication and trading experience (Liu et al., 2010).

Focusing on mutual funds, Bailey et al. (2011) find that investors who exhibit higher scores of narrow framing are less likely to invest in both equity mutual funds and index funds. This might suggest that investors who suffer from narrow framing may have less willingness to invest in P-ETFs.

A particular case of underdiversification is the local bias, i.e., the situation in which investors overweight stocks from one geographical area within their portfolio because these stocks look more familiar—geographically, culturally or socially. In addition to the home bias initially pointed out by French and Poterba (1991), investors have preferences for companies with geographical or professional proximity (e.g., Bailey et al. (2011), Boyle et al. (2012), Massa and Simonov (2006)). Moreover, both cultural distance and language play a role, as shown in Grinblatt and Keloharju (2001a). Building on this

stream of literature, we expect a negative relationship between retail P-ETF investment (or its magnitude) and local bias.

Therefore, regarding the four above-mentioned behavioral biases, we posit our last two hypotheses as follows.

H2. Retail investors who suffer more from behavioral biases are less likely to invest in P-ETFs.

H2*. Among the users of P-ETFs, those who suffer more from behavioral biases trade P-ETFs less often.

2.3 Data and sample

2.3.1 Data

Our data come from an online Belgian brokerage house and cover the trading accounts of 26,140 retail investors over the period January 2003–March 2012. For each investor, we have detailed trading records (ISIN code, timestamp, trade direction, executed quantity, trade price, explicit transaction costs, etc.). For P-ETFs, we count 22,376 trades involving 3,484 retail investors (i.e., 13.33% of the retail investors). These P-ETF users trade 313 different P-ETFs, among which 196 are equities-linked and 72 commodities-linked.¹⁰

In addition to the trading data, we matched individual data that were either sociodemographic (age, gender, education, and spoken language) or survey-based. The descriptive statistics of the sociodemographics are provided in Subsection 2.3.2. The survey-based data comprise subjective investor characteristics¹¹ collected by the brokerage house within the context of the European MiFID regulation. In short, this piece of regulation has made it compulsory for investment firms to collect specific information about their

¹⁰The list of the ten most-traded P-ETFs in the sample is given in Table 6.1 in appendix.

¹¹These survey data are reported online by each investor. Hence, answers are self-reported decisions that investors make on their own, without any interaction with a financial intermediary. Since most of these data imply self-assessment, we consider them subjective characteristics.

retail clients' needs and preferences. Accordingly, investment firms operating in the EU are obliged to submit questionnaires (which are then referred to as "MiFID tests") to their clients. Specifically, two tests are used depending on the client's request: (1) the Appropriateness test (hereafter, the A-test) and (2) the Suitability test (hereafter, the S-test). Investors who ask for financial advice and/or portfolio management services have to fulfil the S-test, which aims at assessing their level of knowledge and experience, their investment objectives and their financial situation.¹² Investors who ask only for order execution (without advice or portfolio management services) have to fulfil the A-test when trading "complex" instruments. This lighter test aims to ensure that the investor has the necessary experience and knowledge to understand the risks involved in these "complex" financial instruments.

For the purpose of this study, we distinguish between "subjective" variables, which are based on the aforementioned A-test and S-test, and "objective" variables, which characterize the actual trading activity of retail investors. In addition, we build several behavioural variables, i.e., proxies used to characterize overconfidence, narrow framing, lack of diversification, and local bias. The descriptive statistics about our subjective variables are provided in Subsection 2.3.2. The objective variables are presented in Subsection 2.3.2, while the behavioural variables are described in Subsection 2.3.2.

2.3.2 Descriptive statistics

As in Bhattacharya et al. (2017) and Bailey et al. (2011), we classify as a P-ETF user any investor who traded a P-ETF at least once over the whole sample period (i.e., 2003-2012). To drop outliers, we use trading experience as filter and we exclude investors with less than 5-month trading experience to disregard very short-lived investors as in

¹²Such items are usually covered in investment policy statements (IPSs) used in portfolio management delegation. There are some points according to Boone and Lubitz (2004) that are primordial for an IPS: 1) client goals and objectives, 2) client fears and concerns, 3) investment time frame, 4) expected mortality, 5) retirement time frame, 6) shorter-term financial needs, 7) risk tolerance attitudes, and 8) risk capacity. In our data, the S-test covers almost all those points.

Glaser and Weber (2009) or Bellofatto et al. (2018).

Sociodemographic variables

The set of sociodemographics includes age, gender, education and spoken language.¹³ We build dummy variables for gender (a dummy set to 1 for men), education (a dummy set to 1 if the investor holds a university degree or equivalent) and language (one dummy set to 1 for each language). All these variables will be used as usual control variables in the ZINB regression model in Section 2.4.

Table 2.1 reports the summary statistics for these sociodemographics, with a distinction between P-ETF users and non-users. P-ETF users are on average somewhat older than non-users (50.32 for P-ETF users versus 47.91 for non-users). The proportion of men is high and similar in the two subsamples, i.e., 87% among P-ETF users versus 86% among non-users. Although statistically significant at the 5% level, this difference is negligible. Regarding education, the proportion of investors who hold a university degree is significantly higher among the P-ETF users than among non-users (80% versus 69%). Regarding spoken language, the proportion of Dutch speakers is the highest in both subsamples (53% and 51%). The proportion of French speakers is exactly the same (42%) in both subsamples, while the proportion of English speakers is slightly higher among the P-ETF users (7% versus 5%). Figure 2.1 displays the histogram of cross-sectional means of sociodemographics for P-ETF users and non-users.

¹³Belgium has three official languages: French, Dutch and German. French and Dutch are spoken the most. On the online trading platform, investors can choose from three available languages: French, Dutch and English.

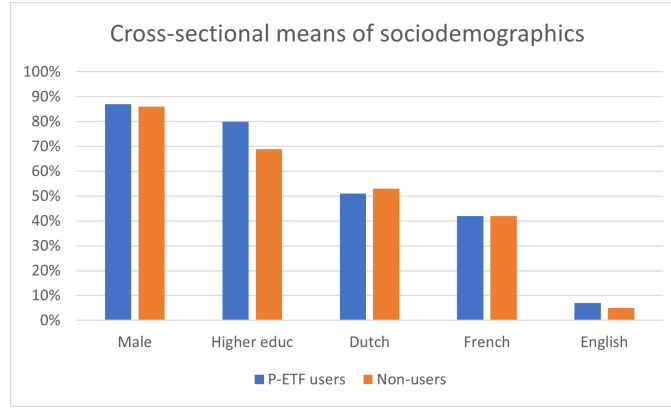


Figure 2.1: Histogram of cross-sectional means of sociodemographics.

This figure shows the distribution of investors according to gender, higher education and language speaking. The horizontal axis refers to P-ETF users and non-users, while the vertical axis refers to the percentage of investors.

Table 2.1: Descriptive statistics for sociodemographics

Metrics		P-ETF users			Non-users			Diff
		Mean	Std Dev	N	Mean	Std Dev	N	
Age (2012)	Years	50.32	13.40	3,484	47.91	13.24	22,656	2.41***
Gender	Dummy=1 if male	0.87	0.33	3,484	0.86	0.35	22,656	0.01**
Higher education	Dummy=1 if university	0.80	0.41	3,484	0.69	0.46	22,656	0.11***
Dutch-speaking	Dummy=1 if Dutch	0.51	0.50	3,484	0.53	0.50	22,656	0.02**
French-speaking	Dummy=1 if French	0.42	0.49	3,484	0.42	0.49	22,656	0.00
English-speaking	Dummy=1 if English	0.07	0.26	3,484	0.05	0.21	22,656	0.02***

This table reports the cross-sectional means, standard deviations, mean differences, as well as the number of investors among the P-ETF users and non-users. For each investor, 'Age' is determined as the difference between 2012 and the year of birth. 'Gender' is a dummy variable equal to one if the investor is a male. 'Higher education' is a dummy variable set to one for investors with a university degree or equivalent. 'Dutch-speaking', 'French-speaking' and 'English-speaking' are three additional dummies based on the language selected by the investor on the online trading platform. *, **, and *** indicate that the means significantly differ at the level of 10%, 5% or 1%, respectively.

Subjective variables

We use the two MiFID questionnaires to define several subjective variables. This is motivated by evidence in the literature regarding the better information content of subjective measures of sophistication, in particular with respect to financial literacy, as for example in Robb and Woodyard (2011), Xiao et al. (2011), Allgood and Walstad (2016), Anderson et al. (2017), and Lind et al. (2020).

Table 2.2 gives the number of investors who completed the A-test and the S-test, with a distinction between P-ETF users and non-users. All the investors filled in the A-test,¹⁴ but only 49.11% of them also completed the S-test. Note that the brokerage house did not offer portfolio management services over the sample period. Hence, the investors completed the S-test to be granted free access to a financial advice tool on stocks. This online tool provided investors with general information on stocks, analysts' reports, and professional recommendations. A total of 61.48% of the investors who took the S-test are P-ETF users.

Table 2.2: Number of completed A-tests and S-tests

	Number of investors	S-test	A-test
P-ETF users	3,484	2,142 61.48%	3,484 100.0%
Non-users	22,656	10,696 47.21%	22,656 100.0%
Total	26,140	49.11%	100.0%

This table reports the number of P-ETF users and non-users as well as the number and percentage of completed A-tests and S-tests, depending on whether the investor is a P-ETF user or not.

Using the A-test data, we summarize the available items into four variables, which allows us to attribute for each of them a final score to each investor. We follow the same approach with the S-test data and gather the available information into five variables. Table 2.3 displays the resulting subjective variables in Panel A for the A-test and in Panel B for the S-test. Figure 2.2 displays the histogram of cross-sectional means of subjective variables for P-ETF users and non-users.

¹⁴The brokerage house that provided us with the data implemented the A-test for an exhaustive list of instruments, including shares traded on a non-European market or on a European non-regulated market (such as Multilateral Trading Facilities under the MiFID typology). Because of this precautionary principle, all the retail investors who traded in the post-MiFID period (i.e., after November 2007) took the A-test.

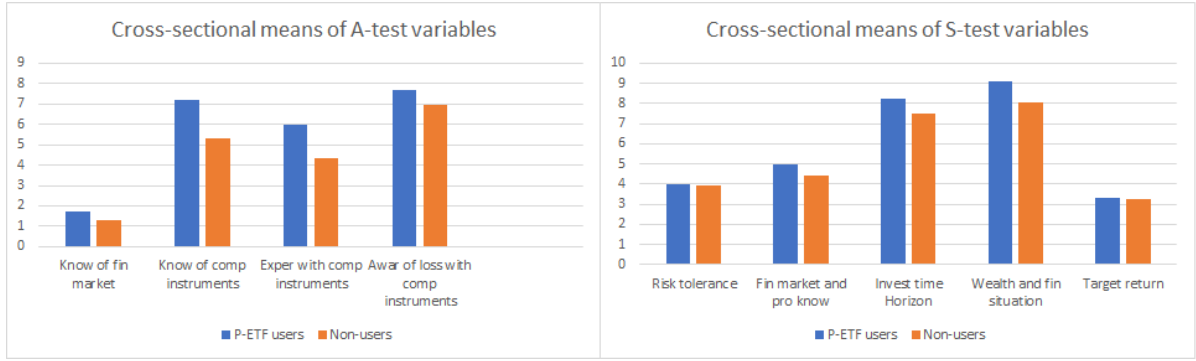


Figure 2.2: Histogram of cross-sectional means of subjective variables.

This figure shows the distribution of investors according to subjective variables. The horizontal axis refers to P-ETF users and non-users, while the vertical axis refers to the score. The right histogram for the S-Test variables and the left histogram for the A-Test variables.

Table 2.3: Descriptive statistics for subjective variables

Metrics		P-ETF users			Non-users			Diff
		Mean	Std Dev	N	Mean	Std Dev	N	
Panel A: Appropriateness Test		(Score Min-Max)						
Knowledge of financial markets	(score 0-3)	1.72	0.89	3,484	1.29	0.97	22,656	0.43***
Knowledge of “complex” instruments	(score 0-18)	7.22	5.78	3,484	5.32	5.39	22,656	1.89***
Experience with “complex” instruments	(score 0-18)	5.96	5.69	3,484	4.33	5.16	22,656	1.63***
Awareness of the losses with “complex” instruments	(score:0-9)	7.67	2.74	3,484	6.96	3.43	22,656	0.71***
Panel B: Suitability Test		(Score Min-Max)						
Risk tolerance	(score 1-5)	3.99	0.91	2,142	3.91	0.95	10,696	0.08***
Financial markets and products knowledge	(score 0-7)	5.01	1.35	2,142	4.41	1.43	10,696	0.60***
Investment time horizon	(score 2-11)	8.24	2.44	2,142	7.51	2.67	10,696	0.73***
Wealth and financial situation	(score 0-17)	9.09	3.58	2,142	8.07	3.63	10,696	1.02***
Target return	(score 1-5)	3.30	1.01	2,142	3.26	1.07	10,696	0.08*

This table provides the cross-sectional means, standard deviations, mean differences, as well as the number of investors among the P-ETF users and non-users. Panel A refers to the A-test, while Panel B refers to the S-test. 'Knowledge of financial markets' refers to one specific question where investors have to self-assess their knowledge of financial markets on a scale of four levels: Level 0 is associated with a basic knowledge, while Level 3 refers to an experienced investor 'who manages any aspect of the financial markets'. For 'Knowledge of "complex" instruments', 'Experience with "complex" instruments' and 'Awareness of the losses with "complex" instruments', the score elicits the investor's self-assessment regarding his/her own abilities and skills. For example, a score of 18 out of 18 for the item 'Knowledge of "complex" instruments' means that the investor considers himself/herself as an expert in the field. Conversely, a score of 0 (out of 18) indicates that the investor declares having no knowledge about "complex" instruments. For 'Risk tolerance', 'Financial markets and products knowledge', 'Investment time horizon' and 'Wealth and financial situation', the score reflects the investor's direct self-assessment regarding the item. 'Target return' refers to the annual yield investors expect on their investments, selected on scale of 5 levels, of which level 1 corresponds to 'a yield without any risk of capital loss' and level 5 to 'the inflation rate + more than 12% per year'. *, **, and *** indicate that the means significantly differ at the level of 10%, 5% or 1%, respectively.

Panel A of Table 2.3 shows that P-ETF users clearly display a higher financial literacy than non-users. This holds for both the knowledge of financial markets in general and the knowledge, experience and awareness about "complex" instruments in particular. The mean score of P-ETF users regarding the 'Knowledge of financial markets' is 1.72,

while the corresponding mean for non-users is only 1.29. Similarly, when focusing on “complex” instruments, P-ETF users (1) exhibit a relatively higher level of knowledge (7.22 vs 5.32); (2) have more experience (5.96 vs 4.33); and (3) are more aware of the risk of incurring losses (7.67 vs 6.96). All these differences are statistically significant at the 1% level.¹⁵

Consistent with Panel A, Panel B of Table 2.3 reveals that P-ETF users display better financial literacy than non-users (5.01 vs 4.41). Moreover, P-ETF users exhibit on average a slightly higher risk tolerance than non-users (3.99 vs 3.91). P-ETF users also have a higher average score for both the items ‘Investment time horizon’ and ‘Wealth and financial situation’. This means that P-ETF users are, on average, wealthier and have a longer investment horizon than non-users. Again, all these differences are statistically significant at the 1% level. Nevertheless, the level of target return appears to differ much less between the two subsamples.

Objective variables

Using the trading data, we first rebuild the end-of-month individual portfolios and then compute a set of objective variables aiming at characterizing the actual trading activity on stocks. Building on prior empirical research, we compute the following variables for each investor: (1) number of stock trades over the whole sample period; (2) trading experience in months, expressed as the number of months between the first and last trades on stocks (e.g., Nicolosi et al. (2009), Bellofatto et al. (2018)); (3) number of different stocks traded (NDST) over the entire sample period (e.g., Feng and Seasholes (2005), Koestner et al. (2017)); (4) trade duration computed as the average number of days between two consecutive trades on stocks (e.g., D’Hondt and Roger (2017)); (5) average number of stocks held in end-of-month portfolios; (6) stock trading intensity (STI),

¹⁵For subjective variables, we opt for Wilcoxon signed-rank tests, which are an appropriate nonparametric alternative to the t-test.

which is a dummy variable equal to one if the investor’s monthly portfolio turnover¹⁶ is in the upper quartile of the sample and equals zero otherwise; and (7) underperformance on stocks (UPS), which is equal to one when the investor’s net excess Sharpe ratio on stocks is in the lower quartile of the sample and equals zero otherwise.¹⁷

Table 2.4 shows that both the ‘Number of stock trades’ and the ‘Number of different stocks traded’ exhibit a higher mean (almost double) for P-ETF users than for non-users, i.e., 133.6 and 33.87 for P-ETF users versus only 71.94 and 17.27 for non-users. This reveals that P-ETF users not only trade twice as many stocks but also trade on a set of different stocks that is twice as large as that of non-users. P-ETF users also exhibit a longer trading experience than non-users (56 versus 46 months). In addition, P-ETF users display a shorter trade duration on average (57 days for P-ETF users vs 91 days for non-users), suggesting that P-ETF users trade stocks more frequently. Furthermore, the typical P-ETF user holds an eight-stock portfolio, while the typical non-user holds a five-stock portfolio. Interestingly, the proportion of P-ETF users with intense trading activity on stocks is lower than that of non-users. Similarly, the proportion of underperformers is approximately 5 percentage points lower among P-ETF users than among non-users. All these differences are highly significant (both economically and statistically) and overall indicate that P-ETF users are more experienced traders on stocks than non-users.

¹⁶Following the approach of ? and Bellofatto et al. (2018), the portfolio turnover is measured as the sum of all the purchases and sales in a particular month divided by the average of the portfolio values at the beginning and end of this month. Barber and Odean (2001) and Koestner et al. (2017) also use turnover to measure what they call overtrading.

¹⁷As in Bellofatto et al. (2018), we calculate the net Sharpe ratio in excess of the Sharpe ratio of the market. This performance measure is computed using the Eurostoxx 600 index as the market portfolio and the 12-month Belgian T-bill rate as the risk-free rate.

Table 2.4: Descriptive statistics for objective variables

Metrics		P-ETF users			Non-users			Diff
		Mean	Std Dev	N	Mean	Std Dev	N	
Number of stock trades		133.6	295.5	3,484	71.94	161.8	22,656	61.67***
Trading experience	(in months)	56.43	27.36	3,484	46.43	26.63	22,656	10.00***
Number of different stocks traded (NDST)		33.87	38.38	3,484	17.27	21.09	22,656	16.60***
Trade duration	(in days)	57.07	96.40	3,484	91.12	158.5	22,656	-34.05***
Number of stocks		8.28	8.37	3,484	4.84	5.30	22,656	3.44***
Stock trading intensity (STI)	Dummy=1 if turnover $\geq$ Q3	0.220	0.414	3,484	0.245	0.430	22,656	-0.025***
Underperformance on stocks (UPS)	Dummy=1 if Net excess Sharpe ratio $\leq$ Q1	0.203	0.402	3,484	0.257	0.437	22,656	-0.054***

This table reports the cross-sectional means, standard deviations, mean differences, and number of investors, with a distinction between P-ETF users and non-users. 'Number of stock trades' is the total number of trades executed on stocks. 'Trading experience' is computed as the difference between the last and the first trading dates, expressed in number of months. 'Number of different stocks traded' (NDST) is the number of different stocks traded. 'Trade duration' is computed as the average number of days between two consecutive trades on stocks. 'Number of stocks' is the average number of stocks held in the end-of-month portfolio. 'Stock trading intensity' (STI) is a dummy variable set to one if the investor's monthly portfolio turnover (i.e., the average of the absolute values of all the purchases and sales in a particular month divided by the average of the portfolio values at the beginning and the end of this particular month) is in the upper quartile of the sample and set to zero otherwise. 'Underperformance on stocks' (UPS) is dummy variable equal to one when the investor's net excess Sharpe ratio on stocks is in the lower quartile of the sample and equal to zero otherwise. All these variables are defined over the whole sample period (i.e., January 2003–March 2012). *, **, and *** indicate that means significantly differ at the level of 10%, 5% or 1%, respectively.

Behavioral variables

Since it is well established in the literature that individuals tend to suffer from several behavioural biases, we compute additional variables in order to capture some of these biases.

First, we estimate overconfidence with the two aforementioned objective variables measuring stock trading intensity and stock underperformance, as in Odean (1999), Barber and Odean (2001), and Bailey et al. (2011). Combining both measures, we create our overconfidence proxy, which is a dummy variable equal to one when the investor simultaneously trades stocks intensively and underperforms (i.e., when the two dummies are set to one) and equal to zero otherwise.

Second, we adopt the approach of Kumar and Lim (2008) and Bailey et al. (2011) by using the degree of clustering in the investors' trades to measure narrow framing.¹⁸ For each investor i , we compute trade clustering (TC_i) as $1 - (\text{number of trading days}_i / \text{number of trades}_i)$. However, because TC_i is correlated with portfolio size, number of stocks, and

¹⁸These authors especially identify whether an investor executes trades separately (i.e., one trade at a time) or executes multiple trades simultaneously.

trading frequency, we use the adjusted measure based on the peer group (ATC_i),¹⁹ and this measure is computed as $TC_i - \text{mean trade clustering of the peer group}$. A positive (negative) value for ATC_i indicates that the trades of investor i are more (less) clustered than those of their counterparts who have the same number of stocks, the same trading frequency and a similar portfolio size. Based on ATC_i , we build a dummy variable to capture narrow framing, where the latter is equal to one when the ATC_i is less than zero and equal to zero otherwise.²⁰

Third, we use two proxies to assess underdiversification. On the one hand, trading underdiversification is based on the number of different stocks traded during the whole period, which reflects how broad the investor's universe of stocks is (Bellofatto et al., 2018). More specifically, we consider that an investor suffers from a lack of diversification when his/her set of different stocks traded is in the lower quartile. On the other hand, we use the monthly average Herfindahl-Hirschman index (HHI hereafter) to build our second proxy aiming at capturing portfolio underdiversification. Building on Goetzmann and Kumar (2008) and Koestner et al. (2017), this index is equal to the sum of the squared stock portfolio weights. It ranges from 0 for well-diversified portfolios to 1 for portfolios including only one stock. Our second proxy is set to 1 when the investor's monthly HHI falls in the upper quartile of the sample and is set to zero otherwise.

Finally, we also compute for each investor the local bias ratio, which captures the concentration of his/her trades on the Belgian stock market and on those of neighbouring countries. As in Bailey et al. (2011), we compute this ratio over the full sample period as the aggregate number of trades on companies headquartered in the home and neighbouring countries (Belgium, France, Netherlands, Germany and Luxembourg) divided by the total number of trades. By construction, this ratio ranges between 0 and 1 and is equal to one when all trades are executed on stocks issued in these five countries.

¹⁹A peer group is made of investors who are in the same quartile in terms of portfolio size, trading frequency, and the number of stocks. An investor can belong to one of the sixty-four groups.

²⁰Kumar and Lim (2008) states that "a low TC measure for an investor indicates that her trades are temporally separated and thus the degree of narrow framing is likely to be higher. In particular, the trade-clustering measure is zero for investors who execute each trade on a separate day. These investors are more likely to adopt narrow decision frames in their investment choices".

Table 2.5 reports the cross-sectional statistics for the above behavioural variables. Overall, P-ETF users look less prone to behavioural biases. The proportion of overconfident investors is higher among non-users than among P-ETF users (10.5% versus 7.2%). This is consistent with Table 2.4, wherein both stock trading intensity and underperformance prevail more among non-users (25% and 26% versus 22% and 20%). For the lack of diversification, the two proxies indicate that P-ETF users suffer less from this bias than non-users. The proportion of P-ETF users (non-users) whose set of stocks traded belongs to the lower quartile is approximately 7% (17%). Similarly, the proportion of P-ETF users (non-users) whose monthly HHI is in the upper quartile is approximately 14% (28%). For the local bias, the average ratio is slightly higher among non-users than among P-ETF users (0.750 versus 0.725). This suggests that the trades executed by non-users are more locally concentrated than those completed by P-ETF users. All these differences are statistically significant at the 1% level. The only exception is narrow framing, for which no significant difference is found between the two subsamples. Figure 2.3 displays the histogram of cross-sectional means of behavioural variables for P-ETF users and non-users.

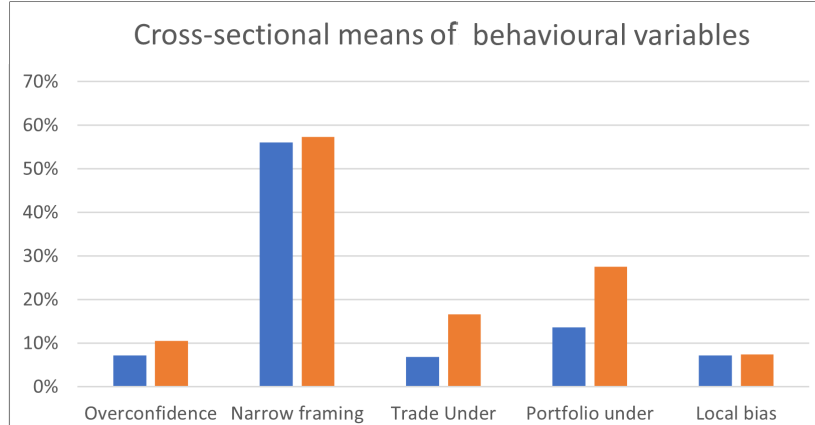


Figure 2.3: Histogram of cross-sectional means of behavioural variables.

This figure shows the distribution of investors according to behavioural variables. The horizontal axis refers to P-ETF users and non-users, while the vertical axis refers to the percentage of investors.

Table 2.5: Descriptive statistics for the behavioural variables

Metrics		P-ETF users			Non-users			Diff
		Mean	Std Dev	N	Mean	Std Dev	N	
Overconfidence	Dummy=1 if STI=1 & UPS=1	0.072	0.258	3,484	0.105	0.306	22,656	-0.033***
Narrow framing	Dummy =1 if ATC<= 0	0.561	0.496	3,484	0.574	0.494	22,656	-0.014
Trade underdiversification	Dummy=1 if NDST <= Q1	0.069	0.254	3,484	0.166	0.373	22,656	-0.097***
Portfolio underdiversification	Dummy=1 if HHI >= Q3	0.137	0.334	3,484	0.276	0.447	22,656	-0.139***
Local bias ratio	(score between 0 & 1)	0.725	0.254	3,484	0.751	0.297	22,656	0.026***

This table reports the cross-sectional means, standard deviations, mean differences, as well as the number of investors, with a distinction between P-ETF users and non-users. 'Overconfidence' is a dummy variable set to one if the investor displays both overtrading ('Stock trading intensity' (STI) is set to one) and underperformance ('Underperformance on stocks' (UPS) set to one), and is set to zero otherwise. 'Narrow framing' is a dummy variable set to one if the investor's adjusted trade clustering (defined as trade clustering minus the mean of trade clustering of the peer group) is less than zero and is set to zero otherwise. 'Trade underdiversification' is a dummy variable set to one if the investor's number of different traded stocks is in the lower quartile and set to zero otherwise. 'Portfolio underdiversification' is a dummy variable set to one if the investor's monthly HHI (defined as the sum of the squared stock portfolio weights) is in the upper quartile and set to zero otherwise. 'Local bias ratio' is computed for any investor as the number of trades executed on stocks issued in the home (Belgium) and in neighbouring countries (France, Netherlands, Germany, and Luxembourg) divided by the total number of trades. *, **, and *** indicate that means statistically differ at the level of 10%, 5% or 1%, respectively.

2.4 Empirical results

To identify the key drivers of the retail P-ETF investors' profile, we opt for a zero-inflated negative binomial (ZINB) model (Lambert, 1992). Such a model allows us to not only determine the probability for an investor to invest in P-ETFs but also explain the magnitude of retail investment in these instruments. This "two-step-in-one" approach is innovative compared with the approaches used in the prior empirical research on investment funds. Bailey et al. (2011) opt for a binary logistic model to examine whether a combination of behavioural factors impact the use of mutual funds by individuals. Bhattacharya et al. (2017) also uses a logit model to study the drivers of retail participation in passive ETFs, while Müller and Weber (2010) prefers a probit model to investigate the drivers of ETF/index fund awareness and choice.

The dependent variable in our ZINB model is the total number of trades on P-ETFs for each investor.²¹ Hence, the basic idea behind this ZINB regression model is that the

²¹Since our dependent variable can take integer values (count data), Poisson regression models could be considered adequate. However, there is a dominance of zeros in our data. Approximately 83% of the retail investors in our database have no trade on P-ETFs, which would make the adoption of a Poisson regression inconsistent. The ZINB model is a modified Poisson regression model used to tackle

decision to invest in P-ETFs and the positive counts of trades in P-ETFs are generated by separate processes. This is appropriate for our retail investor sample that includes two distinct groups: the group of investors who do not invest in P-ETFs (non-users) and the group of investors who invest in P-ETFs to a small or large extent (P-ETF users). Figure 2.4 displays the histogram of distribution of number of P-ETF trades.

In other words, the zero-inflated negative binomial (ZINB) regression is used for count data that exhibit overdispersion and excess zeros. The data distribution combines the logit distribution which takes into consideration the excessive number of zeros and the negative binomial distribution for strictly positive values, as you can see in Figure 2.4.

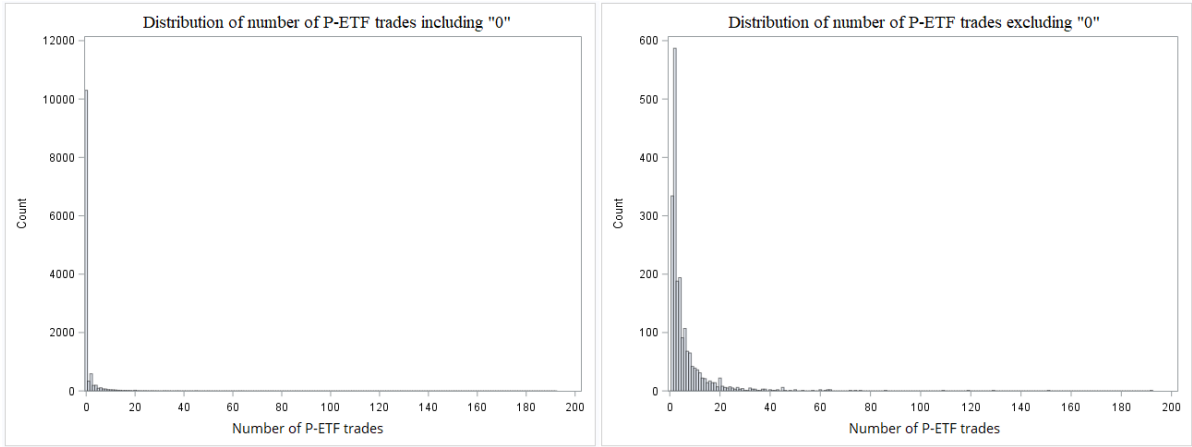


Figure 2.4: Histogram of distribution of number of P-ETF trades.

This figure shows the distribution of investors according to the number of passive ETF trades. The horizontal axis refers to the number of P-ETF trades, while the vertical axis refers to the number of investors. The left graph includes investors with no P-ETF trade, while the right graph excludes investors with no P-ETF trade.

Building on Cameron and Trivedi (2013), the ZINB model can be specified as:

$$P[y = j] = \begin{cases} \pi + (1 - \pi)f_2(0), & \text{if } j = 0 \\ (1 - \pi)f_2(j), & \text{if } j > 0, \end{cases}$$

two common issues in Poisson regressions for count data (e.g., Ridout et al. (1998); Sheu et al. (2004); Burger et al. (2009)). The first issue is overdispersion in the sample, which means that the sample variance is larger than the sample mean, while the variance of the Poisson distribution must be equal to its mean. The second issue is related to an excess of zeros, i.e., the situation in which there is an excessive number of observations equal to 0 (Greene, 2000).

where the base count density is the negative binomial distribution $f_2(y)$,²² y is the number of P-ETF trades, and j is any nonnegative value. To inflate the probability of a zero, we add a separate component, $\pi = f_1(0)$ such that the probability π depends on a set of regressors in a binary logistic model.²³ The ZINB model can be viewed as a weighted mixture of two components, $\pi = f_1(0)$ and $f_2(y = 0)$, used to predict the probability for $j = 0$, i.e., the probability of belonging to the group of non-users. The ZINB model is reduced to $(1 - \pi)f_2(j)$ if the number of P-ETF trades is strictly positive, characterizing the probability of trading P-ETFs at least once.

Table 2.6 presents the results for three specifications of the above ZINB model, with a distinction between the logit ($\pi = f_1(0)$) and the negative binomial regression ($f_2(y)$) components. These results are based on 12,838 observations, i.e., 12,838 retail investors. Panel A refers to the sociodemographics that are included in the three specifications (Model 1, Model 2, and Model 3). Panel B refers to the subjective variables (from the S-test)²⁴ that are also used in the three models. Among them, we are especially interested in the variable "Financial markets and products knowledge" since it is directly related to hypotheses H1/H1* about financial literacy. Panel C is devoted to a set of objective variables added in both Model 2 and Model 3. These variables are useful to test hypotheses H1/H1* about financial experience. Panel D refers to proxies for different behavioural biases available in Model 3. In particular, these variables allow us to test H2/H2* about overconfidence, narrow framing, underdiversification, and about local bias.

A key point regarding the interpretation of the ZINB models is that the signs of the coefficient estimates from the binary logistic equation are often in the opposite direction

²² $f_2(y) = P(y | x) = \frac{\Gamma(y_i + \theta)}{\Gamma(\theta)\Gamma(y_i)!} \mu_i^\theta (1 - \mu_i)^{y_i}$, where $\theta > 0$, $y_i = 0, 1, 2, \dots$, $\mu_i = \frac{\theta}{(\theta + \lambda_i)}$, $E(y_i) = \lambda_i$ and $Var(y_i) = \lambda_i(1 + \alpha\lambda_i)$.

²³ $\pi = f_1(0) = P(y = 0 | x) = G(\beta_0 + \beta_1 x_1 + \dots + \beta_k x_k) = G(\beta_0 + \mathbf{x}\beta_k)$ with $G(\cdot)$ being the logistic cumulative distribution function, where $G(z) \in]0, 1[$ for all $z \in \Re$, and $G(z) = \exp(z) / [1 + \exp(z)]$.

²⁴ Whether the A-test is instead considered in the regression analysis does not change the empirical conclusions regarding the tested hypotheses. The advantage of the S-test is the wider coverage in terms of the risk-return profile of the investor. The A-test strictly focuses on financial knowledge and awareness.

Table 2.6: Results of the ZINB model

Parameter	Model 1				Model 2				Model 3			
	Logit		Negative Binomial		Logit		Negative Binomial		Logit		Negative Binomial	
	Coefficient	OR	Coefficient	IRR	Coefficient	OR	Coefficient	IRR	Coefficient	OR	Coefficient	IRR
Dependent variable												
Number of P-ETF trades												
Independent variables												
Panel A : Sociodemographic variables												
Gender_male (Dummy)	-0.001	0.999	0.059	1.061	-0.004	0.996	-0.027	0.973	0.006	1.006	-0.021	0.979
Age (in Years)	-0.009***	0.992	0.021***	1.021	0.001	1.001	0.011***	1.011	0.001	1.001	0.011***	1.011
Higher education (Dummy)	-0.313***	0.731	0.118	1.126	-0.259***	0.772	0.173**	1.188	-0.258***	0.772	0.162**	1.175
Dutch-speaking (Dummy)	0.055	1.056	-0.118	0.888	0.120*	1.127	-0.018	0.982	0.129*	1.138	-0.011	0.989
English-speaking (Dummy)	-0.442**	0.643	0.224	1.252	-0.426***	0.653	0.453***	1.572	-0.384***	0.681	0.376***	1.457
Panel B : Subjective variables (S-test)												
Financial markets and products knowledge (score 0-7)	-0.287***	0.751	0.151***	1.163	-0.244***	0.784	0.121***	1.128	-0.242***	0.785	0.115***	1.122
Target return (score: 1-5)	0.066*	1.068	-0.140***	0.870	0.084**	1.088	-0.148***	0.863	0.098***	1.103	-0.140***	0.869
Risk tolerance (score 1-5)	0.168***	1.182	0.088**	1.092	0.144***	1.154	0.053	1.054	0.138***	1.148	0.044	1.045
Investment time horizon (score 2-11)	-0.078***	0.925	0.004	1.004	-0.055***	0.947	0.032**	1.033	-0.053***	0.949	0.036**	1.036
Wealth and financial situation (score 0-17)	-0.026**	0.974	-0.001	0.999	-0.008	0.992	0.005	1.005	-0.008	0.992	0.002	1.002
Panel C : Objective variables												
Log(Trading experience)					-0.233***	0.792	0.259***	1.295	-0.212***	0.809	0.341***	1.407
Log(Trade duration)					0.020	1.021	-0.574***	0.563	0.034	1.035	-0.604***	0.547
Log(Number of stocks)					-0.516***	0.597	-0.486***	0.615	-0.487***	0.614	-0.463***	0.630
Stock trading intensity (STI)					-0.143	0.867	-0.355***	0.701	-0.235**	0.790	-0.420***	0.657
Underperformance on stocks (UPS)					0.045	1.046	0.078	1.081	-0.091	0.913	-0.008	0.993
Panel D : Behavioral variables												
Overconfidence									0.392**	1.479	0.257	1.293
Narrow framing									-0.039	0.962	-0.015	0.985
Trade underdiversification									-0.020	1.020	0.700***	2.014
Portfolio underdiversification									0.140	1.150	-0.031	0.969
Local bias ratio									0.297**	1.345	-0.308**	0.735
α (dispersion)	3.32***	27.51			2.05***	7.81			2.00***	7.389		
N	12,838				12,838				12,838			
%(Number of P-ETF trades >0)	16.68%				16.68%				16.86%			
Log likelihood	-11,237				-10,929				-10,906			
AIC	22,520				21,924				21,897			
BIC	22,691				22,170				22,218			

This table reports the results of three ZINB regressions, with a distinction between the logistic and negative binomial components. The dependent variable is the number of P-ETF trades. Panel A refers to the sociodemographics as the usual control variables. 'Gender' is a dummy variable equal to one if the investor is a male. 'Age' is determined as the difference between 2012 and the investor's year of birth. 'Higher Education' is a dummy variable set to one for investors with a university degree (or equivalent). 'Dutch-speaking' and 'English-speaking' are both dummies based on the language selected by the investor on the online trading platform. Panel B includes the subjective variables (from the S-test). For 'Financial markets and products knowledge', 'Risk tolerance', 'Investment time horizon' and 'Wealth and financial situation', the score reflects the investor's direct self-assessment regarding the item. 'Target return' refers to the annual yield investors expect on their investments, selected on scale of 5 levels, of which level 1 corresponds to 'a yield without any risk of capital loss' and level 5 to 'the inflation rate + more than 12% per year'. Panel C includes the objective variables characterizing trading activity. 'Trading experience' is computed as the difference between the last and the first trading dates, expressed in number of months. 'Trade duration' is computed as the average number of days between two consecutive trades on stocks. 'Number of stocks' is the average number of stocks held in the end-of-month portfolio. 'Stock trading intensity' (STI) is a dummy variable set to one if the investor's monthly portfolio turnover (i.e., the average of the absolute values of all the purchases and sales in a particular month divided by the average of the portfolio values at the beginning and the end of this particular month) is in the upper quartile of the sample and set to zero otherwise. 'Underperformance on stocks' (UPS) is dummy variable equal to one when the investor's net excess Sharpe ratio on stocks is in the lower quartile of the sample and equal to zero otherwise. Panel D refers to behavioural variables. 'Overconfidence' is a dummy variable set to one if the investor displays both overtrading (STI is set to one) and underperformance (UPS set to one) and is set to zero otherwise. 'Narrow framing' is a dummy variable set to one if the investor's adjusted trade clustering (defined as trade clustering minus the mean trade clustering of the peer group) is less than zero and set to zero otherwise. 'Trade underdiversification' is a dummy variable set to one if the investor's number of different traded stocks is in the lower quartile and set to zero otherwise. 'Portfolio underdiversification' is a dummy variable set to one if the investor's monthly HHI (defined as the sum of the squared stock portfolio weights) is in the upper quartile and set to zero otherwise. 'Local bias ratio' is computed for any investor as the number of trades executed on stocks issued in the home (Belgium) and in neighbouring countries (France, Netherlands, Germany, and Luxembourg) divided by the total number of trades. 'IRR' is the incidence rate ratio, which is equal to the exponential of the coefficient estimate. 'OR' is the odds ratio, which is equal to the exponential of the coefficient estimate. *, **, and *** indicate that the coefficient estimate is statistically significant at 10%, 5% or 1%, respectively.

to the signs of the coefficient estimates in the count (negative binomial) equation (Long et al., 2006). In our specific case, the logistic process predicts the probability of not investing in P-ETFs; i.e., a negative coefficient estimate implies a higher probability of being a P-ETF investor. In contrast, the negative binomial process predicts the number of P-ETF trades; i.e., a positive coefficient estimate indicates a higher magnitude of P-ETF investment.

2.4.1 The probability of retail investing in P-ETFs

Table 2.6 provides results that are consistent across the three model specifications. We therefore focus on the significant predictors in the logit component of Model 3.²⁵

Regarding the sociodemographics in Panel A, the two dummies 'Higher education' and 'English-speaking' significantly impact the probability of investing in P-ETFs. On the one hand, retail investors who hold a university degree are more likely to invest in P-ETFs. More precisely, the odds of *not* investing in P-ETFs decrease by a meaningful factor of 0.772 for a highly educated retail investor compared to investors who are not highly educated. All else equal, this means the odds of *not* investing in P-ETFs decrease by 22.8% for retail investors with a university degree.²⁶ On the other hand, the odds ratio is even lower (at 0.681) when we consider the marginal effect of the language selected on the trading platform. All else equal, the odds of *not* investing in P-ETFs decrease by 31.9% for English-speaking investors compared to French-speaking investors.²⁷

In Panel B, four subjective variables (out of five) significantly impact the probability of investing in P-ETFs. Focusing first on the variable "Financial markets and products

²⁵The overdispersion parameter α (2.00) is statistically significant at the 1% level for the three ZINB models, which provides strong support for a negative binomial model (instead of a Poisson model). Regarding the goodness of fit, Table 2.6 shows that Model 3 is improved, with the log likelihood increasing (by 345 between Models 1 and 3). Model 3 also displays the lowest AIC and BIC values.

²⁶If retail investors without university degree are used as the reference group, it implies that the odds of *not* investing in P-ETFs increase by 29.5% ($=1/0.772 - 1$) for these retail investors compared to retail investors who hold a university degree.

²⁷In contrast, the odds of *not* investing in P-ETFs increase by 46.8% ($=1/0.681 - 1$) for French-speaking retail investors compared to English-speaking investors.

knowledge', we validate the first dimension of **H1** on the positive impact of financial literacy since its coefficient estimate is negative and statistically significant at 1%. The corresponding odds ratio indicates that the odds of *not* investing in P-ETFs decrease by 21.5% for retail investors who self-report high financial knowledge. Three other subjective variables also exhibit insightful coefficients. A higher 'Target return' by one score unit is associated with a higher probability of *not* investing in P-ETFs all else being equal.²⁸ In other words, the higher the return targeted by retail investors is, the less likely they are to invest in P-ETFs. Regarding 'Risk tolerance', we observe that the more risk tolerant retail investors are, the less likely they are to invest in P-ETFs. All else equal, retail investors who display higher risk tolerance by one score unit have a 1.148 times higher chance of *not* investing in P-ETFs than those who do not. Interestingly, a one-unit increase in the score of 'Investment time horizon' is associated with a decrease of the odds of *not* investing in P-ETFs by a factor of 0.949 all else being equal. We conclude from Panel B that the retail investors who are more likely to invest in P-ETFs are those who are more financially literate, target lower returns, are less risk tolerant, and declare a longer investment horizon, all else equal.

In Panel C of Table 2.6, the coefficient estimate of 'Trading experience' (in log)²⁹ is significant and exhibits a negative sign. We therefore validate the second dimension of **H1** on the positive relationship between financial experience and the probability of investing in P-ETFs.³⁰ Two other objective measures of trading activity are also significant. All else equal, the 'Number of stocks' held in the end-of-month portfolio is positively associated with the probability of investing in P-ETFs, since the odds ratio is equal to 0.614. This is also the case for the variable 'Stock trading intensity', which means that retail investors who trade stocks intensively are more likely to invest in P-ETFs. The odds of *not* investing in P-ETFs for an investor who trades stocks intensively

²⁸All else equal, this means that retail investors who target higher returns by one score unit have a 1.103 times higher chance of *not* investing in P-ETFs than those who do not.

²⁹Based on Glaser and Weber (2009), we use the natural logarithm of the trading experience, the trade duration, the average number of stocks held in a portfolio, and the turnover, since all these variables are positively skewed.

³⁰All else equal, this means that the odds of *not* investing in P-ETFs decrease by 19.1% when the retail investors' trading experience doubles.

decrease by a factor of 0.79. In summary, we learn from Panel C that the retail investors who are more likely to invest in P-ETFs are those who are more experienced, hold a larger number of different stocks in their portfolio, and trade these stocks more intensively (*ceteris paribus*).

For the influence of behavioural biases, Panel D in Table 2.6 shows that two of them, 'overconfidence' and 'local bias', emerge as significant drivers of the probability of investing in P-ETFs. Both negatively affect the chance for a retail investor to trade P-ETFs. We therefore validate two components of **H2**. Specifically, when retail investors are overconfident, their odds of *not* investing in P-ETFs increase by 47.9%. This finding is in line with Bailey et al. (2011), who report that even though overconfident investors have higher allocations in mutual funds, they have a smaller proportion of their equity portfolio invested in index funds because they focus more on actively managed funds. Regarding the local bias, when retail investors invest (exclusively) locally, their odds of *not* investing in P-ETFs also increase by a slightly lower percentage equal to 34.5%. When it comes to the narrow framing bias, we may expect a negative marginal effect on the likelihood of investing in P-ETFs, and as explained in the literature review. This bias is part of mental accounting which helps people keep things, i.e., individual stocks in our case, under control when they are separated. When retail investors decide to invest in P-ETFs, it may mean that they accept to lose control of things, which is contrary to the concept of mental accounting. Finally, we do not find any supportive evidence regarding 'narrow framing' and 'underdiversification'.³¹ Hence, we conclude from Panel D that the retail investors who are less likely to invest in P-ETFs are those who are overconfident and invest locally.

³¹When the interaction term between 'age' and 'underdiversification' is added in the model, it nevertheless shows that the combination of those two characteristics matters, as older investors who underdiversify their stock portfolio are more likely to invest in P-ETFs than the others. No significant evidence is found in the negative binomial section.

2.4.2 The magnitude of P-ETF investment

Unlike the ZINB model’s logit component that is estimated on the full sample of retail investors (including those who do not trade P-ETFs), the negative binomial component is estimated on the subsample of P-ETF users. The latter represents 13.33% of the retail investors in the entire sample. The purpose here is to identify the factors that truly drive the magnitude of P-ETF investment among retail investors who trade P-ETFs.

In Panel A of Table 2.6, higher education and the use of English are again significant drivers. All else equal, both are positively correlated with the magnitude of P-ETF investment. Their respective coefficient estimates are positive, and their incidence rate ratios (IRRs) are greater than 1.³² Specifically, P-ETF users who hold a university degree complete 17.5% more P-ETF transactions on average than those who do not hold such a degree. Similarly, the P-ETF users who selected English on the trading platform execute on average 45.7% more trades on P-ETFs than the French-speaking P-ETF users. Interestingly, investor age also determines the number of P-ETF trades to a lesser extent.³³ We conclude from Panel A that the magnitude of P-ETF investment is stronger when the retail investors are highly educated, English-speaking, and older.

When focusing on Panel B, we observe that the magnitude of P-ETF investment is impacted by the same three subjective variables that drive the probability of trading P-ETFs. We first validate **H1*** since the coefficient estimate of the “Financial markets and products knowledge” variable is positive and significant. The number of P-ETF trades increases by 12.2% for each score unit increase in financial literacy, which is economically substantial. Second, the number of P-ETF trades is positively associated with longer investment time horizons of retail investor: for each score unit increase in the variable

³²The odds ratio is only appropriate when the dependent variable is a dummy variable. The incidence rate ratio (IRR) is the equivalent measure in the negative binomial regression where the dependent variable takes any nonnegative values. The IRR corresponds to the exponential of the coefficient estimate and measures the estimated percentage change in the number of P-ETF trades for each unit variation in the explanatory variable. For example, $IRR = 2$ means that the estimated number of the dependent variable doubles for each unit increase in the explanatory variable.

³³When age increases by 1 year, P-ETF trades are expected to increase by 1.01%.

“Investment time horizon”, the number of P-ETF trades increases by 3.6%. Next, P-ETF users who target higher returns complete a lower number of P-ETF trades. For each score unit increase in the variable “Target return”, the number of P-ETF trades decreases by a sizeable factor of 0.869 (i.e., -13.1%). From Panel B, we conclude that P-ETF users who self-report higher financial literacy, longer investment horizons, and lower target returns trade P-ETFs more often.

Panel C in Table 2.6 reveals that P-ETF users who are more experienced trade P-ETFs more frequently, which validates once more **H1***. Specifically, the coefficient estimate indicates that the number of P-ETF trades increases by 40.7% when trading experience (in months) doubles. In addition, three other drivers negatively affect the magnitude of P-ETF investment, namely, the trade duration on stocks, the number of stocks in the end-of-month portfolio, and the stock trading intensity. When P-ETF users hold a low number of stocks that they do not trade in quick succession in a stock portfolio whose turnover is low, they are more likely to trade P-ETFs more intensively. This suggests a trade-off between the magnitude of P-ETF investment and the magnitude of stock investing. P-ETF users who trade P-ETFs more often not only hold a lower number of stocks but also modify the composition of their stock portfolio less extensively. This points to a substitution effect between stocks and P-ETFs.

For the behavioural variables available in Panel D of Table 2.6, the local bias is the only one that negatively impacts both the probability and the magnitude of investing in P-ETFs. More specifically, trading activity in P-ETFs is 26.5% (i.e., 1 minus 0.735) lower for P-ETF users who suffer more from local bias than for those who suffer less. **H2*** is therefore validated for these bias. By contrast, when considering trading underdiversification, we reject **H2***, albeit partially. All else equal, the number of P-ETF trades increases by 101.4% for P-ETF users who concentrate their stock trading on a few stocks (compared to those P-EFT users who do not). This is totally consistent with the findings of Panel C regarding the substitution effect between stocks and P-ETFs. This result is also in line with Bellofatto et al. (2018), who find that investors with higher

financial literacy tend to concentrate their stock portfolio more extensively and achieve diversification through investment fund holdings. For the remaining biases, there is no evidence to support **H2***. Of particular interest, overconfidence does not appear to drive the magnitude of P-ETF investment, although it affects the probability of trading P-ETFs.

2.4.3 Robustness check

All the models were estimated using the full sample of retail investors and the entire period January 2003-March 2012. However, since the MiFID regulation came into force in late 2007, investors who started trading before MiFID enforcement have accumulated some trading experience before completing the MiFID questionnaires. This experience might influence their answers as well as their behavior in the post-MiFID period, i.e., from January 2008 to March 2012. As a robustness check, we ran the same three models on a subsample excluding all investors who started trading before January 2008. The purpose was to check whether the information content of the MiFID survey data (captured in Panel B) remained unchanged. Overall, the main findings are similar and we notice only a few changes. In Model 3, two variables lose their significance in the Logit part, i.e., 'Dutch-speaking' and 'log(Trading experience)', while three variables are no more significant in the negative binomial part of Model 3, i.e., 'Higher education', 'English-speaking' and 'Stock trading intensity'. These empirical results are available in Table 6.2 in appendix.

We also examine if our findings are sensitive to the specific periods of time during which each retail client is invested in the ETF market. To do so, we include different dummies in our negative binomial models for count data where the dependent variable is the number of P-ETF trades. First, 'Trading P-ETFs before MiFID' is a dummy variable equal to one if the investor had trade P-ETFs before introduction of MiFID (01/11/2007). Second, 'Time before trading P-ETFs' is computed as the number of months between the date of the first trade and the date of the first P-ETF trade. Finally, 'year2003' to 'year2012'

are dummies for the year of the first P-ETF trade (where ‘year2003’ is the reference category). All the models were estimated using sub-sample of investors with at least one P-ETF trade (a strictly positive count), and adding individually and collectively 3 independent variables to capture the retail investors moment of participation in Panel F of Table 6.3. We find that the empirical results remain robust and do not modify anything regarding our variables of interest, as shown in Table 6.3 in the Appendix.

2.4.4 Avenues for future research

Regarding avenues for future research, the present Chapter mainly explores the profile of P-ETF retail investors. There is arguably a few other angles of this topic that still need to be explored. A very interesting question is related to the evolution (or not) of the profile of P-ETF retail investors over time, where the goal is to investigate any potential persistence or changes in the way they keep investing in ETFs. Another research question that can be interesting to explore, is to verify how P-ETF investors with different profiles behave in stressful market conditions, such as bear markets or financial crises, in comparison to normal market conditions.

2.5 Conclusion

To our knowledge, this study is the first of its kind to profile retail investors by using both trading and survey-based data on a large sample over nearly a decade. Such a data set allows us to include a large set of sociodemographic factors, subjective characteristics, trading activity measures, and behavioural variables. We build on the literature and formulate two main hypotheses to test whether retail investors who invest in P-ETFs differ from those who do not. To further contribute to the prior empirical research on investment funds, we opt for a zero-inflated negative binomial (ZINB) regression model to identify the main drivers of retail investment in P-ETFs. The advantage of

this approach is twofold since it enables us to explain the likelihood of retail investors trading P-ETFs as well as the magnitude of the retail investment in P-ETFs.

There is overall strong evidence that retail P-ETF investment is made by more sophisticated investors. When focusing on the likelihood of trading P-ETFs, we find that retail investors who are better educated, self-report both higher financial literacy and a longer investment horizon, exhibit longer trading experience, hold a better diversified stock portfolio, and trade stocks more intensively are more likely to invest in P-ETFs. By contrast, retail investors who declare higher target returns and suffer more from either overconfidence or local bias are less likely to invest in P-ETFs.

We identify similar drivers when we zoom in on the subsample of P-ETF users to analyse the extent to which they trade these products. Higher education, the use of English, higher financial literacy, longer investment horizons, lower target returns, and stronger financial experience are all factors that boost the magnitude of P-ETF investment. In addition, the most active investors in P-ETFs are older and less subject to local bias. Nevertheless, overconfidence does not appear to drive the magnitude of P-ETF investment, although it affects the probability of trading P-ETFs.

Finally, a trade-off seems to exist among P-ETF users between the magnitude of their P-ETF investment and the magnitude of their stock investment. Retail investors who trade P-ETFs more intensively hold a lower number of stocks in their end-of-month portfolio and modify the composition of their stock portfolio less extensively. This particular result points to a substitution effect between stocks and P-ETFs as the trading in P-ETFs increases. We might conjecture that the most active P-ETF users apply a core-satellite portfolio strategy, in which P-ETFs are the core and stocks represent the satellite. Further research is obviously needed to better identify such a strategy as well as its performance.

Chapter 3

Trading behavior of passive ETF retail investors

Chapter Abstract

Although passive exchange traded funds (P-ETFs) have been praised for offering well-diversified and low-cost investment solutions to retail investors, they have also been blamed for not making any difference in terms of performance. We use random matching and rely on both trading records and survey data to better understand P-ETF retail investors' trading behavior. Controlling for all of the key investor characteristics, we find strong evidence that P-ETF retail investors trade differently. They have a larger portfolio size, lower turnover, and they retain their assets for longer periods of time than the reference group of retail investors who hold individual stocks only. P-ETF retail investors show conservative attitude regarding stock gambling, and those among them who invest the most in P-ETFs are the least likely to hold lottery-like stocks.

Keywords: ETFs, Retail Investors, Passive Investing, Gambling Behaviour, MiFID

JEL classification: G11, G40, G53

3.1 Introduction

Exchange traded funds (ETFs) have been gaining ground among institutional and retail investors since their launch in the mid-1990s. As pointed out by Cheng et al. (2018), ETFs have been heralded as “the harbingers of a new era of low-cost/low-risk investment opportunities available to the general public”. Nowadays retail investors can indeed trade a wide range of well-diversified, highly liquid, low-cost funds, allowing them to apply the central tenets of modern portfolio theory.

There have been many arguments in favour of investing in ETFs for households and retail investors. Poterba and Shoven (2002) and Moussawi et al. (2020) show that ETFs are more tax efficient than equity mutual funds. They also offer diversified and low fee portfolios. Oehler and Wanger (2020) provide evidence that plain-vanilla ETFs are suitable instruments to enhance portfolio performance and diversification. These conclusions have been reached by many other authors (see, e.g., Malkiel, 2003; French, 2008; Huang and Lin, 2011; Jacobs et al., 2014; Bhattacharya et al., 2017). All of these benefits explain the substantial shift from active to passive investment (Anadu et al., 2020).

In the literature, a bunch of macro studies have examined the flows in aggregate passive investment vehicles. Sushko and Turner (2018), Easley et al. (2021) and Cheng et al. (2018) show that both index mutual funds and ETFs exhibit high in- and outflows. Sushko and Turner (2018) also document that flows in index mutual funds are less volatile during market turmoil than those in active mutual funds, while it is the opposite for ETFs.¹

In contrast to these macro studies that underscore the high degree of activeness by institutional investors, evidence based on a micro analysis of investment decisions made by retail investors is scarce. Hence, little is known about the way retail investors trade

¹This finding is mainly related to institutional investors. While retail investors trade ETF shares in the secondary market, sophisticated institutional investors influences the process of creation and redemption of shares, which leads to entry and exit of flows (Cheng et al., 2018).

ETFs. Müller and Weber (2010) and Enete et al. (2018) find that ETF users have greater (subjective or objective) financial knowledge than nonusers of ETFs. Da Dalt et al. (2019) provide evidence that households adopt contrarian behaviours when they trade ETFs, although it is even more the case when they trade common stocks.² D’Hondt et al. (2022) find that the most active users of passive ETFs (P-ETFs) hold a smaller number of stocks and modify the composition of their portfolios less extensively, indicating a substitution effect between stocks and P-ETFs. Past research has also identified some pitfalls in the use of ETFs by retail investors. For example, Bhattacharya et al. (2017) report that retail investing in P-ETFs does not improve portfolio performance because of poor ETF timing and poor ETF selection.³

In this paper, our first objective is to investigate whether retail investors who hold P-ETFs manage their securities differently from those who invest in individual stocks only. If this assumption is not validated, then retail investors would not grasp the contribution of passive investment vehicles to diversification and long-term investing, questioning the whole point of passive investing. Building on past research showing that retail investors who trade ETFs exhibit greater financial knowledge and experience (Müller and Weber, 2010; Enete et al., 2018; D’Hondt et al., 2022), we expect retail investors who trade P-ETFs to display coherent trading behaviors, in line with diversification and long-term investing.

In case retail investors understand the added-value of P-ETFs for long-term investing, then they should trade differently from the typical investors in stocks and protect themselves better against stock gambling. Our second objective is therefore to test whether P-ETF retail investors adopt a safer attitude towards lottery-like stocks. Accordingly, a greater propensity to gamble is expected in the reference group of retail investors who

²These authors also find that positive momentum has a stronger impact on the propensity of households to purchase ETFs rather than common stocks.

³In addition to other costly biases, both poor timing and bad selection have been extensively documented in the past for stocks (e.g., De Bondt and Thaler, 1985; Barber and Odean, 2000; Barber et al., 2008; Barber and Odean, 2013). A large number of empirical studies has indeed provided evidence that the average investor underperforms the market as a result of many behavioural biases (e.g., underdiversification, overconfidence, overtrading, disposition effect, sensation seeking and gambling).

hold individual stocks only.

This paper adds to the abovementioned literature and also contributes to the stream of research on household finance, which has been characterized by a lively debate on how individuals should use financial instruments and markets to achieve their objectives (Guiso and Sodini, 2013). First, our methodological approach differs from previous work since we apply a random matching procedure to fine tune the comparison between the retail investors who hold P-ETFs and a reference group of retail investors who hold individual stocks only. Obtaining target and reference groups with similar covariate distributions helps to reduce bias due to the covariates. Second, we use both trading records and survey-based data provided by a major brokerage firm for a very large set of retail investors over nearly a decade. We are therefore able to provide innovative insights about the P-ETF retail investors' behavior, while controlling for all of the key covariates related to sociodemographic indicators, trading activity, and subjective individual characteristics. Furthermore, it is noteworthy that we do not include a large, albeit heterogeneous, universe of P-ETFs but instead focus on P-ETFs in stocks, which are arguably the best candidates to offer effective and low-cost diversification.⁴

Our main findings can be summarized as follows. Controlling for investor financial knowledge and experience, level of education and portfolio value, we show that retail investors who invest in P-ETFs trade their assets differently from those who only hold individual stocks in their portfolio. In particular, P-ETF users hold more securities and adopt a longer-term perspective with respect to portfolio turnover and asset holding period. Our findings suggest that P-ETF retail investors show quite subtle understanding of diversification, since the lower the weight of P-ETFs in the aggregate portfolio is, the more securities investors hold. Heavy P-ETF investors, that is, those who invest more than 75% of their portfolios in P-ETFs, avoid the inefficiency of adding as many assets to their aggregate portfolio as investors do when trading individual stocks only.

⁴We investigate P-ETFs invested in stocks, i.e., ETFs that track a basket of stocks, belonging to an index or not. We exclude leveraged, inverse, or leveraged-inverse ETFs, i.e., ETFs that have a multiplier different from 1. For an analysis of the behavior of retail investors who invest in leveraged exchange traded products, please see D'Hondt et al. (2020).

Moreover, P-ETF retail investors have 49.3% lower turnover than investors who only trade individual stocks, and the higher the P-ETFs weight in the aggregate portfolio is, the more passive P-ETF investors are.

Regarding investor attitude towards lottery-like stocks, we find that retail investors who hold P-ETFs are less prone to gambling with their stocks. Holding P-ETFs in the portfolio is negatively related to the investor’s propensity to trade lottery-like stocks. This conservative behavior against stock gambling is predominant among heavy P-ETF retail investors who invest more than 75% of their aggregate portfolio in P-ETFs.

The remainder of the paper is organized as follows. In Section 3.2, we describe our data and sample, as well as our propensity score matching procedure. We report our empirical work in Section 3.3. We conclude in Section 3.4.

3.2 Data and sample

3.2.1 Data

The data come from an online Belgian brokerage house and span the period of January 2003-March 2012. They are composed of two different datasets. The first dataset provides detailed information about the retail investors’ trading activity. For the purpose of this study, we selected a sample of 14,134 retail investors who traded stocks only or both stocks and P-ETFs⁵ over the entire 111-month period. Our sample contains 2,613 trades on P-ETFs, of which 71% are purchases and 29% are sales, involving 512 retail investors (i.e., 3.46% of the retail investors in our sample). These 512 P-ETF users traded 128 different P-ETFs. Table 3.1 presents the top 5 P-ETFs in our sample. Almost 43% of the number of trades and 46% of the monetary volume are concentrated in the following three P-ETFs: *LYXOR ETF BEL 20* tracking the Belgian BEL20 index, *LYXOR ETF*

⁵Only equity-linked P-ETFs are considered in this study.

DJ ES50 tracking the Dow Jones Global Titans 50, and *LYXOR ETF CAC40* tracking the French CAC40 index.

Table 3.1: The top 5 P-ETFs in the sample

ETF	Number of trades	Share in %	Volume of trades in €	Share in %
LYXOR ETF BEL 20	616	23.57%	2,276,281.99	8.15%
LYXOR ETF DJ ES 50	260	9.95%	4,844,913.89	17.34%
LYXOR ETF CAC 40	244	9.34%	5,620,972.38	20.12%
LYXOR ETF CHINA	104	3.98%	1,768,459.00	6.33%
LYXOR ETF BRAZIL	99	3.79%	805,011.37	2.88%
Other (123 P-ETFs)	1,290	49.37%	12,622,368.71	45.18%
Total	2,613	100%	27,938,007.34	100%

This table reports the number of trades and monetary volume (in EUR) of the top 5 P-ETFs in our sample. Only equity-linked P-ETFs are kept in this study.

Our sample of investors made 801,656 trades on 7,132 different stocks. Unsurprisingly, they are net buyers, since 60% of the trades are purchases, and 40% are sales. Table 3.2 presents the top 5 stocks in our sample, representing approximately 20% of both the total number of trades and the total monetary volume.

Table 3.2: The top 5 stocks in the sample

ETF	Number of trades	Share in %	Volume of trades in €	Share in %
FORTIS	44,453	5.55%	435,646,299	6.55%
KBC	38,035	4.75%	391,576,680	5.89%
DEXIA	36,393	4.54%	312,713,163	4.70%
NYRSTAR	20,990	2.62%	118,290,778	1.78%
AGFA-GEVAERT	14,416	1.80%	95,555,536	1.44%
Other (7,127 stocks)	647,369	80.75%	5,295,868,287	79.64%
Total	801,656	100%	6,649,650,743	100%

This table reports the number of trades and the monetary volume (in EUR) for the top 5 stocks in our sample.

The second dataset complements the first one with more qualitative information about the retail investors: (1) sociodemographic indicators including year of birth, gender, level of education and spoken language;⁶ and (2) survey-based data from two MiFID questionnaires.⁷ The latter are known as the Appropriateness test (A-test hereafter) and the Suitability test (S-test hereafter). In short, both provide self-reported decisions

⁶The investors may select French, Dutch or English as interaction language on the trading platform.

⁷MiFID stands for the Markets in Financial Instruments Directive. MiFID I (2004/39/EC) is known as the first version of this directive, while a review of it was implemented in January 2018 (known as MiFID II (2014/65/UE)).

that investors make on their own, without any interaction with a financial intermediary. Since most of these decisions imply self-assessment, we consider these survey data to be subjective variables.⁸ Table 3.3 reports a brief description of the variables and investor characteristics that are used in our analyses.

3.2.2 Target and reference groups

Since our main objective is to determine whether P-ETF retail investors trade differently from the other investors who only trade individual stocks, we need to compare measures of trading activity between the two groups of investors. For convenience, the first group is named the target group (TG hereafter), which is composed of the 512 investors in the sample who invested in both individual stocks and P-ETFs. The second group is called the reference group (RG hereafter) and is composed of the remaining 13,622 investors who only invested in stocks. The second-to-last column (Diff-1) in Table 3.4 shows that both groups significantly differ on several characteristics. This means that we must control for these differences before comparing the trading behaviour of investors in both groups.

According to Stuart (2010), when estimating the causal effects based on observational data, it is preferable to replicate the experiment as closely as possible by obtaining target and reference groups with similar distributions of covariates. Hence, we rely on propensity score matching (PSM hereafter) to reduce the selection bias and match our reference and target groups using propensity score probabilities estimated with a logistic regression model. In addition, this approach allows us to obtain two groups of similar size, which makes our comparisons more relevant.

In a nutshell, the PSM approach is used in observational studies to reduce the selection bias by matching subjects based on the probability that they would be assigned to a

⁸The two questionnaires include items usually covered in investment policy statements (IPS) used in portfolio management delegation, such as investment objective and horizon, financial situation, risk tolerance, and financial knowledge and experience.

Table 3.3: Brief description of variables and investor characteristics

Variable	Description	Source
Panel A: Sociodemographic variables		
Age	Determined as the difference between 2012 and the year of birth	Survey data
Gender	Dummy variable equal to one if the investor is a male	Survey data
Higher education (H-educ)	Dummy variable equal to one if the investor holds a university degree or equivalent	Survey data
Dutch speaking (NI-spe)	Dummy variable equal to one if the investor who chooses Dutch as the main language on the online brokerage trading platform	Survey data
French speaking (FI-spe)	Dummy variable equal to one if the investor who chooses French as the main language on the online brokerage trading platform	Survey data
English speaking (En-spe)	Dummy variable equal to one if the investor who chooses English as the main language on the online brokerage trading platform	Survey data
Panel B: Subjective variables		
Knowledge of financial markets (KFM)	Score 0-3, refers to question for which investors must self-assess their knowledge of financial markets on a scale of four levels	Survey data
Knowledge of 'complex' instruments (KCI)	Score 0-18, elicits the investor's self-assessment regarding his/her own abilities and skills	Survey data
Experience with 'complex' instruments (ECI)	Score 0-18, elicits the investor's self-assessment regarding his/her own abilities and skills	Survey data
Awareness of the losses of 'complex' instruments (ACI)	Score 0-9, elicits the investor's self-assessment regarding his/her own abilities and skills	Survey data
Appetite for information (AI)	Dummy variable with a value of 1 if the investor has asked for an access to the information tool on stocks and has completed the S-test and 0 otherwise	Survey data
Panel C: Trades-based variables		
Number of trades	Number of trades executed	Trading records
Number of purchases	Number of purchases executed	Trading records
Number of sales	Number of sales executed	Trading records
Trading volume	Volume of total trades in €	Trading records
Buying volume	Volume of total purchases in €	Trading records
Selling volume	Volume of total sales in €	Trading records
Trading experience	Computed as the difference between the last and the first trading dates, expressed in number of months	Trading records
Trade duration	Computed as the average number of days between two consecutive trades	Trading records
Number of different securities traded	Number of different securities traded	Trading records
Number of trading days	Total number of different trading days	Trading records
Panel D: Portfolio-based variables		
Portfolio size (PS)	Average number of securities held in the end-of-month portfolio	Trading records
Portfolio value (PV)	Monthly average end-of-month portfolio market value in €	Trading records
Turnover (TO)	Average of the absolute values of all of the purchases and sales in a particular month divided by the average of the portfolio values at the beginning and the end of this particular month	Trading records
Portfolio holding period (PHP)	Number of months between the first month with a nonempty portfolio, and the last month with a nonempty portfolio, over the period January 2003-March 2012	Trading records
Asset holding period ratio (AHPR)	Asset average holding period in the portfolio, expressed as a percentage of 'Portfolio holding period'	Trading records

This table provides a brief description of all the variables and investor characteristics that will be used in our analysis. Panel A refers to sociodemographic indicators, Panel B to subjective variables based on the MiFID data, Panel C to trade-based variables and Panel D to portfolio-based variables. In Panels C and D, all the variables are computed over the entire sample period, that is, January 2003-March 2012.

specific group. In our case, the goal is to construct two groups of “comparable” TG investors and RG investors. Specifically, the propensity score is computed for each investor in the sample and is equal to the estimated probability that a given retail investor would trade P-ETFs at least once during the sample period, conditioned on a set of regressors, X . This probability is given by $Prob[Y = 1|X] = G(x'b)$, where $G(\cdot)$ is the logistic cumulative distribution function. Given the data at hand, we opt for a random matching procedure that controls for sociodemographics, portfolio value and subjective variables from the A-test. This leads to the following logit model:

$$P(Y_i = 1|SDV_i; SV_i; OV_i) = G(\beta_0 + \beta_1 SDV_i + \beta_2 SV_i + \beta_3 OV_i + \epsilon_i) \quad (3.1)$$

where the dependent variable, Y_i , is a dummy variable set to 1 when investor i trades P-ETFs at least once over the entire sample period. In the set of explanatory variables, SDV_i is a vector of sociodemographic attributes for investor i , including age, gender, level of education and spoken language; OV_i is an objective variable measuring investor i 's portfolio value in euros; and SV_i is the vector of subjective variables based on survey data, which includes investor i 's financial knowledge and experience.

To obtain relevant estimates of the matching scores, we apply the general-to-specific approach and only retain in Equation 3.1 the significant variables (with a 10% threshold). The resulting model is the following:⁹

$$P(Y_i = 1|X) = G(\beta_0 + \beta_1 \text{ENG}_i + \beta_2 \text{HighEduc}_i + \beta_3 \text{KnowFM}_i + \beta_4 \text{ExpCI}_i + \beta_5 \text{PtfValue}_i + \epsilon_i) \quad (3.2)$$

where ENG_i is a dummy variable equal to 1 when investor i selected English as main language and 0 otherwise; HighEduc_i is a dummy variable equal to 1 when investor i holds a university degree (or equivalent) and 0 otherwise; KnowFM_i refers to one specific question in which investors must self-assess their knowledge of financial markets on a

⁹The results of the logit model 3.2 for propensity score matching are presented in Table 6.4 in the Appendix.

four-level scale, from basic knowledge (Level 0) to large experience allowing to manage any aspect of financial markets (Level 3); ExpCI_i is the investor i 's self-assessment regarding his/her own experience with complex financial instruments; and PtfValue_i is the investor i 's portfolio value (in euros).

There are many ways to match individuals assigned to different groups based on propensity scores.¹⁰ We opt for matching based on an allowable absolute difference between exact propensity scores, i.e., based on a radius around the score matching.¹¹ This method allows us to end up with a sample of 511 investors in the RG (PSM-RG hereafter).

The last column (Diff 2) of Table 3.4 shows that our propensity score matching is successful since all the discriminant variables (e.g., higher education, English speaking, knowledge of financial markets, and portfolio value) are no longer significantly different between the TG and the PSM-RG.¹² The two resulting groups of investors are therefore comparable regarding sociodemographics, subjective variables, and portfolio value. Figure 3.1 displays the histogram of cross-sectional means of sociodemographics and subjective variables for TG and RG before and after PSM.

¹⁰Among them are nearest neighbour matching, radius matching, kernel matching, and interval matching.

¹¹Each treated observation i is matched with control observations j as long as their absolute difference in propensity scores (PS) falls within a specified radius, r , such that $||PS_i - \hat{PS}_j|| < r$. The lower r is, the higher the level of closeness is. In our case, r is set to 0.01. We choose the smallest radius possible to obtain a very similar number of observations to the TG, keeping the differences between the TG and the RG (after PSM) no longer significant.

¹²The five variables reported in bold in Table 3.4 are the ones used to estimate the matching score based on Equation 3.2.

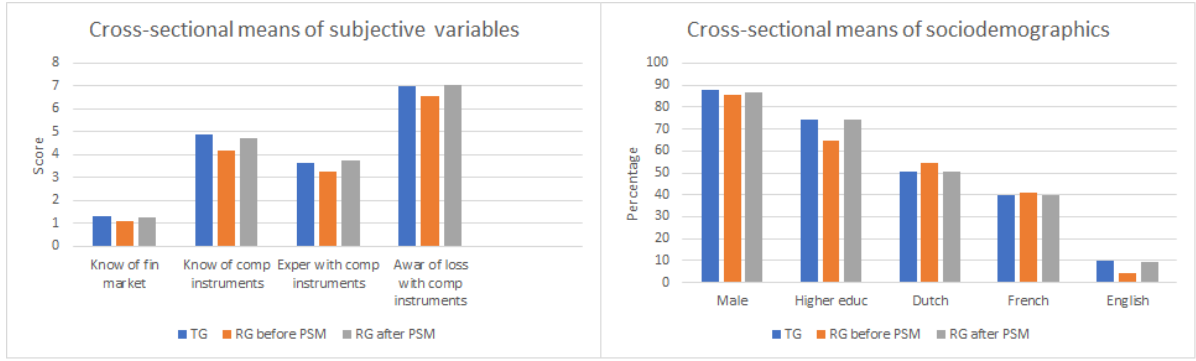


Figure 3.1: Histogram of cross-sectional means of sociodemographics and subjective variables.

This figure shows the distribution of investors according to sociodemographics and subjective variables. The horizontal axis refers to TG and RG, while the vertical axis refers to the score and the percentage. The right histogram for the sociodemographics and the left histogram for the subjective variables.

Table 3.4: Descriptive statistics – before and after the propensity score matching (PSM)

		TG n = 512 (1)		RG before PSM n = 13,622 (2)		RG after PSM n = 511 (3)		t-test	
		Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Diff-1 (1)-(2)	Diff-2 (1)-(3)
Panel A: Sociodemographics									
Age	Years in 2012	47.25	13.03	47.34	13.13	47.72	13.97	-0.093	-0.464
Gender	Dummy=1 if male	0.877	0.329	0.854	0.353	0.867	0.340	0.023	0.010
Higher education (HighEduc)	Dummy=1 if university	0.742	0.438	0.645	0.479	0.742	0.438	0.097***	0.001
Dutch speaking	Dummy=1 if Dutch	0.504	0.500	0.543	0.498	0.507	0.500	-0.039*	-0.003
French speaking	Dummy=1 if French	0.398	0.490	0.412	0.492	0.399	0.490	-0.014	-0.001
English speaking (ENG)	Dummy=1 if English	0.098	0.297	0.045	0.207	0.094	0.292	0.053***	0.004
Panel B: Subjective variables									
		(Score Min-Max)							
Knowledge of financial markets (KnowFM)	(score 0-3)	1.326	0.894	1.071	0.921	1.243	0.899	0.255***	0.084
Knowledge of “complex” instruments	(score 0-18)	4.895	5.067	4.173	4.826	4.708	5.027	0.721***	0.186
Experience with “complex” instruments (ExpCI)	(score 0-18)	3.641	4.819	3.279	4.525	3.752	4.799	0.361*	-0.111
Awareness of the losses in “complex” instruments	(score:0-9)	7.022	3.384	6.588	3.692	7.025	3.356	0.434***	-0.004
Panel C: Objective variable									
Portfolio value (PtfValue)	(in €)	53,244.8	220,615	12,702.0	119,926	38,276.5	225,253	40,542.8***	14,968.3

The table reports the cross-sectional mean, standard deviation and means difference between the TG and the RG before and after propensity score matching. Panel A includes sociodemographics. 'Age' is determined as the difference between 2012 and the year of birth. 'Gender' is a dummy variable equal to one when the investor is a male. 'Higher education' refers to the proportion of investors who held a university degree or equivalent. 'Dutch speaking', 'French speaking' and 'English speaking' refer to the proportion of investors who selected Dutch, French, and English, respectively, as main language on the online trading platform. Panel B includes subjective variables based on the A-test. 'Knowledge of financial markets' refers to one specific question, for which investors must self-assess their knowledge of financial markets on a four-level scale, wherein Level 0 is associated with a basic knowledge and Level 3 refers to an experienced investor “who manages any aspect of the financial markets”. For 'Knowledge of “complex” instruments', 'Experience with “complex” instruments' and 'Awareness of the losses in “complex” instruments', the score elicits the investor's self-assessment regarding his/her own abilities and skills. For example, a score of 18 out of 18 on the item 'Knowledge of “complex” instruments' indicates that the investor considered himself/herself as an expert in the field. Conversely, a score of 0 (out of 18) indicates that the investor declared no knowledge about “complex” instruments. Panel C only includes 'Portfolio value' that is the investor monthly average end-of-month portfolio market value in €. Bold variables are the ones used to estimate the matching score based on Equation 3.2. *, **, *** indicate statistical significance at the level of 10%, 5% or 1%, respectively.

3.2.3 Analyses of trading behaviours

Based on investors' transactions, we compute various metrics to characterize the trading activity of the TG and RGs. The results are presented in Table 3.5.

Table 3.5 reports the univariate tests on mean differences in several trading activity measures between the TG and the PSM-RG. For the TG investors, we distinguish between their P-ETF portfolio, stock portfolio and aggregate portfolio (P-ETFs & stocks), while the PSM-RG investors' portfolio includes only stocks by construction. In Panel A (Diff-4), *Number of trades* and *Trading volume* between the two groups show no significant differences when focusing on the aggregate portfolios. In contrast, the TG displays significantly higher *Trading experience*, *Number of different securities traded*, *Number of trading days*, and lower *Trade duration*. This result display that P-ETF investors have roughly similar trading activeness as individual stock investors for the aggregate portfolio, but they still exhibit very lower trading activeness regarding their P-ETF portfolio. Also, TG investors show higher trading experience, larger universe of securities traded and lower trade duration pointing out higher level of sophistication, and confirming the literature findings.

Panel B in Table 3.5 reveals that TG investors show both significantly higher *portfolio size* and *asset holding period ratio*. The latter measure is defined as the asset average holding period in the portfolio, expressed as a percentage of *Portfolio holding period* which equals the number of months between the first month with a nonempty portfolio, and the last month with a nonempty portfolio, over the sample period (January 2003-March 2012). P-ETF investors seem to hold, on average, three more securities than stock only investors, and they also retain their assets longer. These results display that, firstly P-ETF investors are aware of the importance of the principle of diversification since that in addition to their P-ETFs holdings, which is by definition a basket of securities, they hold on average 2.25 stocks more than PSM-RG investors, secondly P-ETF investors hold their securities for a longer time period, and this is even truer for P-ETFs holdings, proving that they are long run investors and not short run traders, this pointing out

once again their higher sophistication level.

However, neither group shows significantly different trading behaviours regarding *turnover*, *portfolio holding period* and *Portfolio value* of the aggregate portfolio.

All TG investors trade P-ETFs at least once during the sample period, but this fact does not necessarily indicate that they behave similarly. The extent to which they use P-ETFs can lead to heterogeneous behaviours among them. We test whether their behaviours depend on the weight allocated to P-ETFs in their portfolios by creating four sub-TGs (TG1, TG2, TG3 and TG4), in which we cluster TG investors according to the weight of P-ETFs in their aggregate portfolio.¹³ We then perform an analysis of variance (ANOVA hereafter) to investigate whether our measures of trading activity vary significantly across the four sub-TGs, depending on the level of P-ETF weight in their aggregate portfolios. Figure 3.2 displays the histogram of TG investors' distribution according to the weight of P-ETFs in the portfolio.

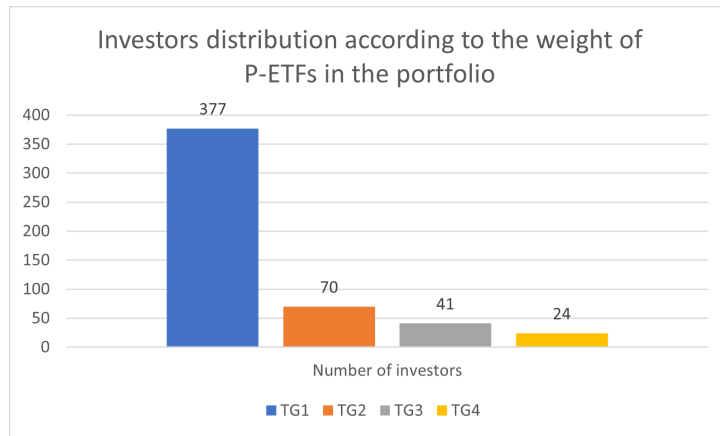


Figure 3.2: Histogram of TG investors' distribution.

This figure shows the distribution of TG investors according to the weight of P-ETFs in their aggregate portfolio.

¹³The goal is to identify 'light, medium and heavy users of P-ETFs' and not to obtain four balanced groups of investors (in contrast to the matching procedure). We therefore do not rely on the use of quartiles, in which each quartile contains 25% of the TG investors by construction. In such a case, the first (second, third) quartile includes investors whose portfolio weight in P-ETFs is less than 12.91%, 27.46%, and 58.83%, respectively. Using these quartiles would have prevented us from identifying 'heavy users' in particular. The results are still reported in Table 6.5 in the Appendix.

Table 3.5: Univariate t -test comparisons between TG and PSM-RG investors.

Metrics		TG n = 512			PSM-RG n = 511		t-test			
		P-ETFs	Stocks	P-ETFs + Stocks	Stocks	Diff-1 (1)-(2)	Diff-2 (1)-(4)	Diff-3 (2)-(4)	Diff-4 (3)-(4)	
		Mean (1)	Mean (2)	Mean (3)	Mean (4)					
Panel A: Trades-based variables										
Number of trades		5.10	62.76	67.86	59.39	-57.65***	-54.28***	3.37	8.48	
Number of purchases		3.63	39.30	42.92	35.21	-35.67***	-31.59***	4.08	7.71*	
Number of sales		2.52	26.40	27.58	26.85	-23.89***	-24.34***	-0.45	0.73	
Trading volume	(in €)	5,638.8	4,770.7	4,975.2	6,055.3	868.1	-416.5	-1,284.6*	-1,080.2	
Buying volume	(in €)	5,522.7	4,666.5	4,829.3	5,753.9	856.3	-231.1	-1,087.4	924.6	
Selling volume	(in €)	7,172.5	5,208.3	5,596.6	6,968.8	1,964.2**	203.7	-1,760.5**	-1,372.1	
Trading experience	(in months)	14.09	45.59	48.08	42.52	-31.51***	-28.44***	3.07**	5.55***	
Trade duration	(in days)	213.9	96.33	66.84	98.08	117.6***	-115.9***	-1.75	-31.24***	
Number of different securities traded		1.65	18.23	19.88	13.38	-16.58***	-11.73***	4.85***	6.50***	
Number of trading days		4.39	41.88	45.04	38.10	-37.49***	-33.71***	3.78	6.94*	
Panel B: Portfolio-based variables										
Portfolio size		1.31	6.25	6.94	4.00	-4.94***	-2.69***	2.25***	2.94***	
Portfolio value	(in €)	12,131.6	45,766.7	53,244.8	38,276.5	-33,635.1***	-26,144.9***	7,490.2	14,968.3	
Turnover		1.57	1.58	1.50	1.38	-0.01	0.18	0.20	0.12	
Portfolio holding period	(in months)	29.59	57.62	59.28	57.63	-28.02***	-28.04***	-0.01	1.64	
Asset holding period ratio (AHPR)		0.93	0.66	0.65	0.61	0.27***	0.32***	0.05***	0.04***	

The table reports the cross-sectional mean and means differences between the TG (P-ETFs, Stocks and aggregate portfolios) and the PSM-RG (Stocks portfolio). For each variable under scrutiny, we report its mean for each group. Panel A includes trades-based variables. 'Number of trades' is the number of trades executed over the sample period. 'Number of purchases' is the number of purchases executed over the sample period. 'Number of sales' is the number of sales executed over the sample period. 'Trading volume' is the volume in (€) of trades executed over the sample period. 'Buying volume' is the volume in (€) of purchases executed over the sample period. 'Selling volume' is the volume in (€) of sales executed over the sample period. 'Trading experience' is computed as the difference between the last and the first trading dates, expressed in number of months. 'Trade duration' is computed as the average number of days between two consecutive trades. 'Number of different securities traded' is the number of different securities traded during the whole period. 'Number of trading days' is the total number of different trading days during the whole trading period. Panel B includes portfolio-based variables. 'Portfolio size' is the average number of securities held in the end-of-month portfolio. 'Value of the portfolio' is the average value of the end-of-month portfolio. 'Turnover' is the average of the absolute values of all of the purchases and sales in a particular month divided by the average of the portfolio values at the beginning and the end of this particular month. 'Portfolio holding period' is the number of months between the first month with a nonempty portfolio, and the last month with a nonempty portfolio, over the sample period (January 2003-March 2012). 'Asset holding period ratio' is asset average holding period in the portfolio, expressed as a percentage of 'Portfolio holding period'. *, **, *** indicate that the difference is statistically significant at the level of 10%, 5% or 1%, respectively.

Table 3.6 reports the ANOVA results for all of the trading activity measures. They are all significant, except for *Portfolio value* and *Turnover*. Panels A and B show a negative relationship between the P-ETF weight and *Number of trades*, *Trading experience*, *Number of different securities traded*, *Number of trading days* and *Portfolio size*, while this relationship is positive with *Trade duration* and *Asset holding period ratio*. There is no clear trend regarding *Trading volume*, although the differences among the four groups are significant. These results display that light, medium and heavy P-ETF investors have in-depth understanding of diversification, since that they hold on average an increasing number of securities as the weight of P-ETFs in the aggregate portfolio goes down. Also, heavy P-ETF investors hold their securities for a longer time period and

trade less than light P-ETF investors, pointing out that they are aware of the nature of financial instrument that they are holding, as they are a long run investors with passive investment behavior, which may help them to grasp the main potential of this financial instrument.¹⁴

Table 3.6: Univariate ANOVA comparisons among TG investors for the aggregate portfolio.

	TG1	TG2	TG3	TG4	
Weight of P-ETFs in the aggregate portfolio	0 – 25%	25% – 50%	50% – 75%	75% – 100%	F-stat
Number of investors	n=377	n=70	n=41	n=24	
	Mean	Mean	Mean	Mean	
Panel A: Trades based variables					
Number of trades	82.80	25.83	25.68	27.79	6.42***
Number of purchases	51.89	17.41	16.85	20.91	7.35***
Number of sales	33.01	11.11	9.78	8.25	3.89***
Trading volume	4,705.0	4,182.8	8,964.7	4,714.5	3.58**
Buying volume	4,563.5	3,999.8	9,066.6	4,184.2	3.86***
Selling volume	5,181.1	4,607.2	10,118.1	7,187.3	3.43**
Trading experience	51.32	38.59	41.54	36.04	8.86***
Trade duration	55.39	91.23	102.75	114.36	10.74***
Number of different securities traded	23.81	9.52	9.10	6.75	20.80***
Number of trading days	54.06	19.93	19.29	20.67	11.08***
Panel B: Portfolio based variables					
Portfolio size	7.94	4.39	4.43	2.94	13.24***
Portfolio value (in €)	59,128.2	29,117.5	59,120.5	21,160.8	0.55
Turnover	1.99	0.17	0.16	0.09	0.20
Portfolio holding period (in months)	61.25	53.13	54.73	53.88	3.22**
Asset holding period ratio (AHPR)	0.62	0.74	0.75	0.76	7.79***

The table reports the results for the analysis of variance (ANOVA) on the relationship between several variables characterizing trading behaviour and the weight of P-ETFs in the aggregate portfolio. For each variable under scrutiny, we report its mean for each TG-i group. Panel A includes trades-based variables. 'Number of trades' is the number of trades executed across the two assets (Stocks and P-ETFs). 'Number of purchases' is the number of purchases executed over the sample period. 'Number of sales' is the number of sales executed over the sample period. 'Trading volume' is the volume in (€) of trades executed over the sample period. 'Buying volume' is the volume in (€) of purchases executed over the sample period. 'Selling volume' is the volume in (€) of sales executed over the sample period. 'Trading experience' is computed as the difference between the last and the first trading dates, expressed in number of months. 'Trade duration' is computed as the average number of days between two consecutive trades. 'Number of different securities traded' is the number of different securities traded during the whole period. 'Number of trading days' is the total number of different trading days during the whole trading period. Panel B includes portfolio-based variables. 'Portfolio size' is the average number of securities held in the end-of-month portfolio. 'Value of the portfolio' is the average value of the end-of-month portfolio. 'Turnover' is the average of the absolute values of all of the purchases and sales in a particular month divided by the average of the portfolio values at the beginning and the end of this particular month. 'Portfolio holding period' is the number of months between the first month with a nonempty portfolio and the last month with a nonempty portfolio, over the sample period (January 2003-March 2012). 'Asset holding period ratio' is asset average holding period in the portfolio, expressed as a percentage of 'Portfolio holding period'. *, **, *** indicate significance at the level of 10%, 5% or 1%, respectively.

¹⁴Additional univariate ANOVA comparisons among TG investors for the core and satellite portfolios are reported in Table 6.9 in the Appendix.

The results in Table 3.6 clearly indicate that TG investors' trading behaviour is linked to the weight of P-ETFs in their aggregate portfolio. We therefore replicate the same univariate t -tests between the PSM-RG and each of the TG subgroups (TG1, TG2, TG3 and TG4) in Table 3.7.

Table 3.7: Univariate t -test comparisons between sub-TG and PSM-RG investors for the aggregate portfolio.

Weight of P-ETF in aggregate portfolio		TG1	TG2	TG3	TG4	PSM-RG	t-test				
		0 – 25% n=377	25% – 50% n=70	50% – 75% n=41	75% – 100% n=24	0% n=511					
	Metrics	Mean (1)	Mean (2)	Mean (3)	Mean (4)	Mean (5)	Diff-1 (1)-(4)	Diff-2 (1)-(5)	Diff-3 (2)-(5)	Diff-4 (3)-(5)	Diff-5 (4)-(5)
Panel A: Trades based variables											
Number of trades		82.80	25.83	25.68	27.79	59.39	55.01***	23.42**	-33.56***	-33.70***	-31.59**
Number of purchases		51.89	17.41	16.85	20.91	35.21	30.97***	16.68***	-17.80***	-18.36***	-14.30
Number of sales		33.01	11.11	9.78	8.25	26.85	24.76***	6.16	-15.74***	-17.07***	-18.60***
Trading volume	(in €)	4,705.0	4,182.8	8,964.7	4,714.5	6,055.3	9.48	-1,350.3*	-1,872.6**	2,909.3	-1,340.9
Buying volume	(in €)	4,563.5	3,999.8	9,066.6	4,184.2	5,753.9	379.4	-1,190.4	1,754.0**	3,312.7	-1,569.7
Selling volume	(in €)	5,181.1	4,607.2	10,118.1	7,187.3	6,968.8	-2,006.1	-1,787.6*	-2,361.5**	3,149.3	218.5
Trading experience	(in months)	51.32	38.59	41.54	36.04	42.52	15.27***	8.79***	-3.94	-0.99	-6.48
Trade duration	(in days)	55.39	91.23	102.75	114.36	98.08	-58.97**	-42.69***	-6.85	4.67	16.28
Number of different securities traded		23.81	9.52	9.10	6.75	13.38	17.06***	10.43***	-3.85***	-4.28***	-6.63***
Number of trading days		54.06	19.93	19.29	20.67	38.10	33.39***	15.96***	-18.17***	-18.83***	-17.43**
Panel B: Portfolio based variables											
Portfolio size		7.97	4.39	4.43	2.94	4.00	5.00***	3.94***	0.39	0.43	-1.06**
Portfolio value	(in €)	59,128.2	29,117.5	59,120.5	21,160.8	38,276.5	37,967.4***	20,851.7	-9,159.0	20,844.0	-17,115.7
Turnover		1.99	0.17	0.16	0.09	1.38	1.90	0.60	-1.22**	-1.22**	-1.30**
Portfolio holding period	(in months)	61.25	53.13	54.73	53.88	57.63	7.37	3.62**	-4.50	-2.90	-3.75
Asset holding period ratio (AHPR)		0.62	0.74	0.75	0.76	0.61	0.14**	0.01	0.13***	0.14***	0.15***

The table reports the cross-sectional mean and means differences between TG-i groups (aggregate portfolios) and PSM-RG (Stocks portfolio). For each variable under scrutiny, we report its mean for each group. Panel A includes trades-based variables. 'Number of trades' is the number of trades executed over the sample period. 'Number of purchases' is the number of purchases executed over the sample period. 'Number of sales' is the number of sales executed over the sample period. 'Trading volume' is the volume in (€) of trades executed over the sample period. 'Buying volume' is the volume in (€) of purchases executed over the sample period. 'Selling volume' is the volume in (€) of sales executed over the sample period. 'Trading experience' is computed as the difference between the last and the first trading dates, expressed in number of months. 'Trade duration' is computed as the average number of days between two consecutive trades. 'Number of different securities traded' is the number of different securities traded during the whole period. 'Number of trading days' is the total number of different trading days during the whole trading period. Panel B includes portfolio-based variables. 'Portfolio size' is the average number of securities held in the end-of-month portfolio. 'Value of the portfolio' is the average value of the end-of-month portfolio. 'Turnover' is the average of the absolute values of all of the purchases and sales in a particular month divided by the average of the portfolio values at the beginning and the end of this particular month. 'Portfolio holding period' is the number of months between the first month with a nonempty portfolio and the last month with a nonempty portfolio over the sample period (January 2003-March 2012). 'Asset holding period ratio' is asset average holding period in a portfolio, expressed as percentage of 'Portfolio holding period'. *, **, *** indicate that the difference is statistically significant at the level of 10%, 5% or 1%, respectively.

In column (Diff-1), we report the t -test statistics for the null hypothesis that the difference in means between the TG1 investors (who invest less than 25% of their aggregate portfolio in P-ETFs) and the TG4 investors (who invest at least 75% of their aggregate portfolio in P-ETFs) is equal to zero. The null is rejected across all of the variables, except for *Trading volume*, *Turnover* and *Portfolio holding period*, confirming that trading behaviours are heterogeneous among TG investors, and this especially true between

light P-ETF investors and heavy P-ETF investors.

In columns (Diff-2) to (Diff-5), we report the t -test statistics for the equivalent null between the PSM-RG and each of the four TGs. Compared to the PSM-RG, *Number of trades*, *Number of different securities traded*, and *Number of trading days* are significantly higher for TG1 and lower for TG2, TG3 and TG4. *Trading volume* and *Trade duration* are on average significantly lower in both TG1 and TG2 (relative to PSM-RG), while *Trading experience* is only significantly higher in TG1. There is overall a very sharp contrast between the way in which the light P-ETF (TG1) investors behave relative to the other groups, including the PSM-RG. The result show how the behavior of medium and heavy P-ETF investors is similar, but still significantly different than individual stocks investors (PSM-RG).

Panel B confirms the sharp contrast in trading behaviours between the PSM-RG and TGs, as well as among them. Relative to the PSM-RG, Portfolio size is, on average, significantly higher in TG1 and significantly *lower* in TG4. There is therefore a significantly negative relationship between the **weight** of P-ETFs in the aggregate portfolio of TG investors and the number of securities held in the portfolio. Light P-ETF investors (TG1) exhibits significantly higher *Portfolio holding period* than the PSM-RG on average. We also see that medium and heavy P-ETF investors (TG2, TG3 and TG4) show a significantly lower mean *Turnover* than the PSM-RG. With respect to *Asset holding period ratio* medium and heavy P-ETF investors (TG2, TG3 and TG4) show significantly higher means than the individual stocks investors (PSM-RG) at the 5% level.¹⁵ Once again the result show how the behavior of medium and heavy P-ETF investors is similar, but still significantly different than individual stocks investors (PSM-RG), as long run investors with passive investment behavior. Figure 3.3 displays the histogram of cross-sectional means of portfolio based variables for TG1, TG2, TG3, TG4 and PSM-RG.

¹⁵Additional comparisons related to the portfolio arithmetic net excess return and the volatility of the two portfolio components (core and satellite) are reported in Table 6.7 in the Appendix.

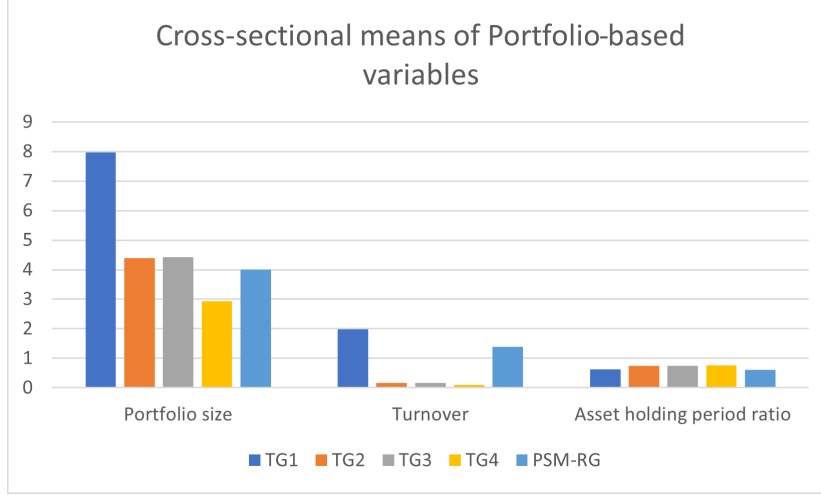


Figure 3.3: Histogram of cross-sectional means of portfolio-based variables.

This figure shows cross-sectional means of portfolio based variables.

3.3 Empirical results

3.3.1 Drivers of heterogeneity in trading behaviours

The previous section provides general insights into the trading behaviour of P-ETF investors. In this section, we extend our analysis to a multivariate framework based on cross-sectional regressions, enabling us to test whether retail investors trade P-ETFs differently than stocks *all else being equal*, i.e., controlling for all of the key individual characteristics such as sociodemographics, financial knowledge and trading based variables.

The regressions include the *TG* dummy, which equal to 1 if the investor is in the TG and 0 otherwise. Four alternative dummies (TG1, TG2, TG3 and TG4) are based on the weight of P-ETFs in the investor's aggregate portfolio, using a 25% range as in the previous section. The use of the four sub-TGs captures the *ceteris paribus* differences in trading behaviours among TG investors observed in the preceding univariate framework, to examine the behavior of light, medium and heavy P-ETF investors behavior separately. Our initial model specification is the following:

$$Trading\ Measure_i = \beta_0 + \beta_1 * TG_i + \beta_2 * SD_i + \beta_3 * SV_i + \beta_4 * OV_i + \epsilon_i \quad (3.3)$$

wherein the dependent variable TM_i is a trading measure for investor i used to proxy his or her trading behaviour. TM_i is in turn *Portfolio size*, $Log(Turnover)$ and *Asset holding period ratio (AHPR)*, as defined in the previous section. The variable of interest is TG_i , which is set to 1 if investor i holds at least one P-ETF in his/her portfolio and 0 otherwise. In alternative specifications, TG_i is replaced by the four sub- TG groups ($TG1$ to $TG4$), as explained above. To control for individual characteristics, we include SD_i as a vector of sociodemographics, which includes age, gender, the level of education and the spoken language of investor i . The second vector, SV_i , includes subjective variables based on investor i 's answers to the A-test. It includes *knowledge of financial markets*, *knowledge of 'complex' instruments*, *experience with 'complex' instruments*, and *awareness of the losses of 'complex' instruments*. The third vector, OV_i , corresponds to objective variables and is based on trading records. It includes the *number of trades*, *trading experience*, *trade duration* and the *number of different securities traded* by retail investor i . All of these variables are further explained in Table 3.3.

Table 3.8 reports models results.¹⁶ In Panel A, the regression on *Portfolio Size* in column (1) provides evidence that TG investors hold more securities than PSM-RG investors. Regression (2) further suggests that there is meaningful heterogeneity among the TGs since the marginal effect of holding P-ETFs on portfolio size decreases as investors hold a larger proportion of their aggregate portfolio in P-ETFs, going from TG1 to TG4. The lower that the weight of P-ETFs in the aggregate portfolio is, the more securities that investors hold. For example, light P-ETF investors whose aggregate portfolios are invested in P-ETFs for at most 25%, hold on average 1.79 securities more than individ-

¹⁶As a robustness check, we also ran the same three models without including Panel D (Objective variables), and the results persist regarding our variables of interest. Our motivation was to check whether those control variables affect the results of our models, since it may appear to be mechanically related to the outcome variables. These empirical results are in 6.8 in the Appendix.

ual stocks (PSM-RG) investors, all else being equal. Therefore, all TG investors hold significantly more securities than PSM-RG investors, except for heavy P-EFT investors (TG4), who are already very diversified by investing at least 75% of their aggregate portfolios in P-ETFs, the coefficient is still positive but not significant. This outcome shows that P-ETF investors are better aware of the need to diversify than PSM-RG investors. Their understanding of diversification is also quite subtle since the TG investors who are the most exposed to P-ETFs (TG4) avoid the inefficiency of adding as many assets to their aggregate portfolios as the PSM-RG investors.

In regressions (3) and (4), we choose $\log(\textit{Turnover})$ as the dependent variable. The marginal effect of the variable of interest TG in regression (3) is significant and negative, indicating that the turnover of the aggregate portfolio is lower when retail investors hold P-ETFs. The retail investors who hold a P-ETF in their aggregate portfolio have a 49.3% lower turnover than investors who only trade stocks, all else equal. All of the coefficient estimates are also statistically negative and decreasing across the TG subgroups, which confirms the negative relationship between the weight of P-ETFs in the aggregate portfolio of TG investors and the *Turnover*, i.e., the higher the P-ETFs weight the more passive retail investors are.

Table 3.8: P-ETF investors' trading behaviours.

		Portfolio size		Log(Turnover)		AHPR	
		(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Variable of interest							
TG	Dummy =1 if P-ETF user	1.507***		-0.493***		0.083***	
TG1	Dummy =1 if P-ETF user in TG1		1.792***		-0.335***		0.074***
TG2	Dummy =1 if P-ETF user in TG2		0.935**		-0.729***		0.103***
TG3	Dummy =1 if P-ETF user in TG3		1.187*		-0.735***		0.108***
TG4	Dummy =1 if P-ETF user in TG4		0.071		-1.419***		0.101**
Panel B: Socio-demographic variables							
Age	Years	0.055***	0.056***	-0.014***	-0.013***	0.003***	0.003***
Gender	Dummy=1 if male	0.012	0.053	-0.031	-0.009	-0.020	-0.021
Higher education	Dummy=1 if university	0.668**	0.0710**	-0.156**	-0.131*	0.074**	0.073***
Dutch speaking	Dummy=1 if Dutch	0.537**	0.556**	-0.190***	-0.183***	0.048***	0.047***
English speaking	Dummy=1 if English	0.278	0.303	-0.471***	-0.449***	0.022	0.020
Panel C: Subjective variables							
Knowledge of financial markets	(score 0-3)	-0.131	-0.148	-0.073*	-0.081**	0.012	0.012
Knowledge of 'complex' instruments	(score 0-18)	0.049	0.053	0.003	0.005	0.000	0.001
Experience with 'complex' instruments	(score 0-18)	-0.034	-0.035	0.015	0.014	-0.002	-0.003
Awareness of the losses of 'complex' instruments	(score 0-9)	0.007	0.001	-0.008	-0.011	-0.004	-0.002
Panel D: Objective variables							
Number of trades		-0.010***	-0.010***	0.005***	0.005***	-0.001***	-0.001***
Trading experience	(in months)	-0.012**	-0.013**	-0.004***	-0.004***	-0.002***	-0.002***
Trade duration	(in days)	-0.000	-0.001	-0.002***	-0.002***	0.001***	0.001***
Number of different securities traded		0.242***	0.237***	-0.002	-0.005***	-0.002***	-0.002***
Intercept		-1.481**	-1.492**	-0.384**	-0.387**	0.514***	0.513***
Adjusted R^2		0.507	0.509	0.383	0.405	0.241	0.240
N		1023	1023	1,023	1,023	1,023	1,023

Note: this table reports the results of cross-sectional regressions in which the dependent variables are the portfolio sizes for models (1) and (2), the logarithm of turnover for models (3) and (4) and the Asset Holding Period Ratio (AHPR) for models (5) and (6). Panel A includes variables of interest. 'TG' is a dummy variable set to 1 if investor holds a P-ETF and 0 otherwise. 'TG1', 'TG2', 'TG3' and 'TG4' are dummies characterizing the weight of P-ETFs in the aggregate portfolio with four intervals of 25% range spread (i.e., [0%-25%], [25%-50%], [50%-75%] and [75%-100%] respectively). Panel B refers to sociodemographics as control variables. 'Age' is determined as the difference between 2012 and the investor's year of 'birth'. 'Gender' is a dummy variable equal to one if the investor is a male. 'Higher Education' is a dummy variable set to one for investors with a university degree (or equivalent). 'Dutch speaking' and 'English speaking' are both dummies based on the language selected by the investor on the online trading platform. Panel C includes subjective variables (from the A-test). 'Knowledge of financial markets' refers to one specific question for which investors must self-assess their knowledge of financial markets on a scale of four levels, wherein Level 0 is associated with a basic knowledge, while Level 3 refers to an experienced investor 'who manages any aspect of the financial markets'. For 'Knowledge of "complex" instruments', 'Experience with "complex" instruments' and 'Awareness of the losses with "complex" instruments', the score elicits the investor's self-assessment regarding his/her own abilities and skills. For example, a score of 18 out of 18 for 'Knowledge of "complex" instruments' indicates that the investor considers himself/herself as an expert in the field. Conversely, a score of 0 (out of 18) indicates that the investor declares no knowledge about "complex" instruments. 'Appetite for information' is binary variable with a value of 1 if the investor has asked for access to the information tool on stocks and has completed the S-test and 0 otherwise. Panel D includes objective variables characterizing trading activity. 'Number of trades' is the number of trades executed over the sample period. 'Trading experience' is computed as the difference between the last and the first trading dates, expressed in number of 'months'. 'Trade duration' is computed as the average number of days between two consecutive trades. 'Number of different stocks traded' is the number of different stocks traded. *, **, *** indicate that the coefficient is statistically significant at the level of 10%, 5% or 1%, respectively.

In regressions (5) and (6), the dependent variable is *Asset holding period ratio* (AHPR). We find that investors who invest in P-ETFs exhibit a significantly higher *asset holding period ratio* than PSM-RG investors, where AHPR it is 7% and 10% points higher for TG1 and TG2-TG4 than PSM-RG investors, respectively, indicating that they hold their assets 'more longer' (in terms of their portfolio holding period) than PSM-RG investors

Regarding covariates and sociodemographics in particular, Panel B in Table 3.8 indicates that three variables, i.e., *Age*, *Higher education* and *Dutch-speaking*, all have a positive and significant impact on *Portfolio size* and *Asset holding period ratio*. Stated differently, older, better educated, Dutch-speaking retail investors have larger portfolio sizes and are less active since they retain their assets for a longer period of time. Correspondingly to the empirical results found for *Asset holding period ratio*, *Turnover* decreases when investors are older, better educated, and either Dutch or English speaking.

In Panel C of Table 3.8, no subjective variable is statistically significant. As discussed in the previous section, this outcome is most likely due to the matching procedure that led to the identification of the PSM-RG. *Financial knowledge and experience* were two key drivers of the matching scores, causing the TG and PSM-RG samples to display almost identical levels. The matching procedure could therefore have completely (and rightly so) emptied the information content of these two variables.

In Panel D of Table 3.8, we find that investors hold a larger number of securities in their end-of-month portfolios (*Portfolio size*) when they make fewer transactions (*Number of trades*) and trade a larger variety of assets (*Number of different securities traded*), which is very much expected. In addition, the more experienced that retail investors are, the smaller that the number of different securities is in their end-of-month portfolios since the coefficient estimate of *Trading experience* is negative (and significant). When *Turnover* is used as the dependent variable, the three significant drivers are *Number of trades*, *Trading experience*, and *Trade duration*. The higher that the trading experience is, the lower that the turnover is. As expected, turnover also decreases when the number of trades or the average number of days between two consecutive trades (*Trade duration*) increases. Finally, we find in model specifications (5) and (6) that investors who are more experienced make more transactions (*Number of trades*), trade a greater diversity of securities (*Number of different securities traded*), or display shorter trade duration hold their assets for a shorter period of time (*Asset holding period ratio*).

To summarize Table 3.8, ‘P-ETF retail investors have different investing behavior’. All

else being equal, retail investors who hold P-ETFs invested in stocks have larger *Portfolio size*, lower *Turnover*, and a higher *Asset holding period ratio* than investors who only hold individual stocks (PSM-RG). We therefore affirm that retail investors who hold P-ETFs trade differently than those who hold only individual stocks, showing a passive and long run investment behavior.

3.3.2 P-ETF investors and stock gambling behavior

Trading and gambling share structural characteristics, sadly enough. Stock gambling can even be an addictive process and a serious disorder in some cases (Grall-Bronnec et al., 2017). Although there is strong evidence that holding P-ETFs implies different trading behaviours, we do not know whether it helps to shield retail investors against stock gambling.

To investigate this possibility, we identify lottery-type stocks at the monthly frequency among all of the stocks traded in our sample.¹⁷ Following Kumar (2009), the stocks that are likely to be perceived as lottery-type stocks are those in the lowest k^{th} stock price percentile, the highest k^{th} idiosyncratic volatility percentile, and the highest k^{th} idiosyncratic skewness percentile.¹⁸

We then estimate individual preference (*gambling preference*) for lottery-type stocks using two metrics. The first measure of preference for lottery-type stocks, LP^1 , for

¹⁷Our identification of lottery-type stocks is based on a universe of 8,097 stocks, and a stock may be considered a lottery-type stock for a specific month and not necessarily over the full sample. Other studies used the same approach as Kumar (2009) for identifying lottery-type stocks. They have used 12,031 stocks in their universe. However, there is no consensus in the literature regarding the minimal required number of stocks in the universe for identifying the lottery-type stocks. For example, Frino et al. (2019) use 2,311 stocks while Fong (2013) uses 4,118 stocks and Meng and Pantzalis (2018) use 22,121 stocks.

¹⁸In Kumar (2009), $k = 50$. Volatility and skewness are computed over 6 months of daily returns. We use total volatility and total skewness in our approach since Kumar (2009) found that the idiosyncratic and total measures provide equivalent results.

investor i in month t , is the *raw portfolio weight* allocated to lottery-type stocks.

$$LP_{i,t}^1 = \frac{\sum_{j \in \zeta_{t-1}} n_{ijt} P_{jt}}{\sum_{j=1}^{N_{it}} n_{njt} P_{jt}} * 100, \quad (3.4)$$

where ζ_{t-1} is the set of lottery-type stocks defined at the end of month $t - 1$, N_{it} is the number of stocks in the portfolio of investor i at the end of month t , n_{njt} is the number of shares of stock j in the portfolio of investor i at the end of month t , and P_{jt} is the price of stock j in month t .

The second measure of lottery-type stock preference that we use is LP^2 based on investor i 's trades.

$$LP_{i,t}^2 = \frac{VBL_{i,t}}{VB_{i,t}} * 100, \quad (3.5)$$

where $VBL_{i,t}$ is the buy volume for lottery-like stocks for investor i in month t , and $VB_{i,t}$ is the total buy volume for all stocks for investor i in month t .

Finally, we estimate four panel data regressions over 111 months (from January 2003 to March 2012) using the sample of 1,023 investors who constituted the TGs and PSM-RG in the preceding sections (P-ETF investors and individual stocks investors). As the dependent variable, we use the two above-defined lottery-type stock preference measures ($LP_{i,t}^1$ and $LP_{i,t}^2$). More specifically,

$$LP_{i,t} = \beta_0 + \beta_1 * TG_{i,t} + \beta_2 * Crisis_t + \beta_3 * SD_i + \beta_4 * SV_i + \beta_5 * OV_i + \nu_i + \mu_t + \epsilon_{i,t} \quad (3.6)$$

where the dependent variable $LP_{i,t}$ is a lottery-stock preference measure for investor i in month t , $TG_{i,t}$ is a dummy variable set to 1 in every month t if investor i holds a P-ETF and 0 otherwise. A negative and significant β_1 indicates that retail investors who are holding a P-ETFs show a cautious behavior against holding speculative stocks. $Crisis_t$ is a dummy variable set to 1 for every month t between September 2008 and June 2009 and 0 otherwise.

As in Equation 4.3, we control for individual characteristics. We add a vector of sociodemographics, SD_i , including age, gender, education level, and spoken language. The second vector is SV_i , corresponding to subjective variables derived from the retail investors' answers given on the A-test. It includes *knowledge of financial markets*, *knowledge of 'complex' instruments*, *experience with 'complex' instruments*, *awareness of the losses of 'complex' instruments* and *appetite for information*. The latter is a dummy variable that equals 1 if the investor has asked for an access to the information tool on stocks and has completed the S-test and 0 otherwise. The third vector, OV_i , corresponds to objective variables and is based on trading records. It includes the *number of trades*, *trading experience*, *trade duration* and *number of different securities traded* by retail investor i . All these variables are further detailed in Table 3.3.

When estimating these panel data regressions, we also cluster standard errors by month and by investor; i.e., we use double-clustered standard errors, which account for two dimensions of within-cluster correlation.¹⁹

To test whether the magnitude of investing in P-ETFs bears on the magnitude of investing in lottery-like stocks, we also estimate the panel model specification below:

$$LP_{i,t} = \beta_0 + \beta_1 * TG1_{i,t} + \beta_2 * TG2_{i,t} + \beta_3 * TG3_{i,t} + \beta_4 * TG4_{i,t} + \beta_5 * Crisis_t + \beta_6 * OV_i + \beta_7 * SDV_i + \beta_8 * SV_i + \nu_i + \mu_t + \epsilon_{i,t} \quad (3.7)$$

where we replace the dummy TG with the four dummies, TG1 to TG4, as defined before in Section 3.2.3. They help to distinguish among light, medium and heavy P-ETF retail

¹⁹The goal of this method is to consider the correlations among different investors in the same month and different months for the same investor. As explained in Thompson (2011), the choice of this approach is based on a trade-off between bias (underestimating the true standard error) and variance. According to Thompson (2011), clustering by time eliminates most of the bias if there are far more firms (here, retail investors) than time periods. Exploring the bias issue, Petersen (2009) found that the bias in the clustered standard error estimates decreases with the number of periods (dropping from 27% when there are only 5 periods to 1% when there are 100 periods). In our case, the number of periods (months) is equal to 111, indicating that we can take advantage of double-clustered standard errors since it is an easy robustness check, and the size of the bias is extremely limited (i.e., the standard error estimates are more accurate).

investors.²⁰ We use exactly the same covariates as in Equation 3.6.²¹

Table 3.9 reports the results for the four panel regressions,²² where the dependent variables are $LP_{i,t}^1$ for models (1) and (2) and $LP_{i,t}^2$ for models (3) and (4).²³

²⁰'TG1', 'TG2', 'TG3' and 'TG4' are dummies characterizing the weights of P-ETFs in the aggregate portfolio with four intervals of 25% range (i.e.,]0%-25%],]25%-50%],]50%-75%] and]75%-100%], respectively)

²¹As a robustness check, we replace the "Crisis" dummy variable by the "% of trades during the 2008 financial crisis" for each investor i . The empirical results remain consistent regarding our variables of interest. The results are reported in Table 6.12 in the Appendix.

²²We also ran the same three models without including Panel D (Objective variables), and the results persist regarding our variables of interest. Our motivation was to check whether those control variables affect the results of our models, since it may appear to be mechanically related to the outcome variables. These empirical results are in 6.10 in the Appendix.

²³In Table 3.2 we can see that the top three stocks in the sample are banking stocks: Fortis, KBC and Dexia. They account for about 14.84% of total number of trades and about 17.14% of total volume of trades. These three banks were arguably considered as reliable investments by Belgian retail investors before the 2008 banking crisis. We therefore investigate the sensitivity of our results by considering the three stocks as non lottery stocks over the whole sample period. In Table 6.11 in the Appendix, we show that the empirical results remain robust and do not modify anything regarding our variables of interest.

Table 3.9: Results of panel regressions

		$LP_{i,t}^1$		$LP_{i,t}^2$	
		(1)	(2)	(3)	(4)
Panel A: Variables of interest					
Hold P-ETF	Dummy =1 if investor hold P-ETF	-0.516***		0.066	
TG1	Dummy if P-ETF user in TG-1		-2.920***		-0.547***
TG2	Dummy if P-ETF user in TG-2		-1.361***		-0.003
TG3	Dummy if P-ETF user in TG-3		-3.663***		-0.300
TG4	Dummy if P-ETF user in TG-4		-5.867***		-0.785***
Financial crisis 2008	Dummy	2.305***	2.292***	1.476***	1.468***
Panel B: Socio-demographic variables					
Age	In years	-0.038***	-0.047***	-0.006***	-0.008***
Gender	Dummy	0.184	0.139	-0.097	-0.109
Higher education	Dummy	-0.723***	-0.736***	-0.267***	-0.272***
Dutch speaking	Dummy	0.019	-0.060	0.112	0.098
English speaking	Dummy	-0.678***	-0.648***	-0.250***	-0.252***
Panel C: Subjective variables					
Knowledge of financial markets	Score 0-3	-0.081	-0.012	-0.067	-0.054
Knowledge of 'complex' instruments	Score 0-18	-0.087***	-0.070***	-0.008	-0.005
Experience with 'complex' instruments	Score 0-18	0.093***	0.063***	0.016	0.011
Awareness of the losses of 'complex' instruments	Score 0-9	0.059***	0.056***	-0.004	-0.004
Appetite for information	Dummy	-0.824***	-0.659***	-0.004	-0.164***
Panel D: Objective variables					
Number of trades		0.386***	0.362***	0.635***	0.630***
Trading experience	(in months)	0.044***	0.045***	0.010***	0.011***
Trade duration	(in days)	-0.002***	-0.003	-0.002***	-0.002***
Number of different securities traded		-0.030***	-0.016***	0.635***	0.011***

Note: this table reports the results of the panel regressions, where the dependent variables are $LP_{i,t}^1$ for models (1) and (2) and $LP_{i,t}^2$ for models (3) and (4). Panel A includes variables of interest. 'TG' is a dummy variable set to 1 if an investor holds a P-ETF and 0 otherwise. 'TG1', 'TG2', 'TG3' and 'TG4' are dummies characterizing the weight of P-ETFs in the aggregate portfolio with four intervals of 25% range spread (i.e., [0%-25%], [25%-50%], [50%-75%] and [75%-100%] respectively). 'Financial crisis 2008' is dummy variable set to 1 if the month is between September 2008 and June 2009 and 0 otherwise. Panel B refers to sociodemographics as control variables. 'Age' is determined as the difference between 2012 and the investor's year of 'birth'. 'Gender' is a dummy variable equal to one if the investor is a male. 'Higher Education' is a dummy variable set to one for investors with a university degree (or equivalent). 'Dutch speaking' and 'English speaking' are both dummies based on the language selected by the investor on the online trading platform. Panel C includes subjective variables (from the A-test). 'Knowledge of financial markets' refers to one specific question for which investors must self-assess their knowledge of financial markets on a scale of four levels, wherein Level 0 is associated with a basic knowledge, while Level 3 refers to an experienced investor 'who manages any aspect of the financial markets'. For 'Knowledge of "complex" instruments', 'Experience with "complex" instruments' and 'Awareness of the losses with "complex" instruments', the score elicits the investor's self-assessment regarding his/her own abilities and skills. For example, a score of 18 out of 18 for the 'Knowledge of "complex" instruments' means that the investor considers himself/herself an expert in the field. Conversely, a score of 0 (out of 18) indicates that the investor declares no knowledge about "complex" instruments. 'Appetite for information' is binary variable with a value of 1 if the investor has asked for an access to the information tool on stocks and has completed the S-test and 0 otherwise. Panel D includes objective variables characterizing trading activity. 'Number of trades' is the number of trades executed over the sample period. 'Trading experience' is computed as the difference between the last and the first trading dates, expressed in the number of 'months'. 'Trade duration' is computed as the average number of days between two consecutive trades. 'Number of different stocks traded' is the number of different stocks traded. *, **, *** indicate that the coefficient is statistically significant at the level of 10%, 5% or 1%, respectively.

We first examine in Panel A the coefficient estimates of the variables of interest, i.e., the TG and the four TGi dummies. There is very strong evidence that holding P-ETFs in portfolios is negatively related to investors' propensity to invest in lottery-type

stocks when it is proxied by the first measure of lottery-stock preference (LP^1). For all the P-ETF-holding dummies in models (1) and (2), we find a negative and statistically significant marginal impact at the 1% level. We therefore affirm that holding P-ETFs on equities reduces the gambling behaviour of retail investors with regard to stock trading. Among holders of P-ETFs, the retail investors who are least likely to hold lottery-like stocks are those who invested the most in P-ETFs, as shown by the coefficient estimate of the TG4 dummy (-5.867).

The use of the second measure of lottery-stock preference (LP^2) is less revealing, but evidence still points in the same direction when statistical significance emerges. The same conclusion is also reached with respect to the light and heavy P-ETF investors since the negative and significant coefficients estimate (-0.547 and -0.785 respectively) is found for dummies TG1 and TG4. The retail investors who are most conservative regarding stock gambling are again those who invest the most in P-ETFs.

An interesting piece of evidence emerges with respect to the dummy *Crisis*. Investors increased their propensity to invest in lottery-like stock during the financial crisis of 2008-2009. This result is in line with Kumar (2009), who find that individual investors prefer stocks with lottery features, and like lottery demand, the demand for lottery-type stocks increases during economic downturns.

In Panel B, three sociodemographic variables (*Age*, *Higher education* and *English-speaking*) have negative impacts on the propensity of investors to invest in lottery-like stocks. Older, better educated and English-speaking investors gamble less with their stocks.

Panel C confirms that our model specification makes economic sense. *Knowledge of 'complex' instruments* and *Appetite for information* display significant and negative coefficient signs. Retail investors with greater knowledge of 'complex' instruments and appetite for information exhibit a lower propensity to invest in lottery-type stocks. This outcome is consistent with Bellofatto et al. (2019), who showed that investors who display an appetite for information tend to make smarter investment decisions than their counterparts. In contrast, the variables *Experience with 'complex' instrument* and

Awareness of the losses of ‘complex’ instruments indicate positive marginal effects on the propensity to invest in lottery-type stocks, which also makes sense since these two variables go beyond the simple knowledge of complex instruments and capture the level of experience retail investors declare to have with complexity and nonlinear risk.

Regarding the objective variables in Panel D, two variables seem to positively impact investors’ propensity to trade lottery-type stocks, i.e., *Number of trades* and *Trading experience*. The more trades that retail investors actually make (or the more active that they are in trading), the more likely that they are to invest in lottery-type stocks (all else equal). Additionally, the longer that their experience in trading is (meaning that they have survived for a longer period of time), the more likely that they are to invest in lottery-type stocks (all else being equal). As expected, the ceteris paribus effect of *Trade duration*, which is a proxy for trading ‘inactivity’, is statistically negative, meaning that a larger average number of days between two consecutive trades decreases the chance of holding a lottery-type stock. Finally, *Number of different securities traded* also exhibits a negative and significant coefficient estimate, suggesting that retail investors who gamble more with their stocks do it in a more concentrated portfolio, again a logical conclusion.

3.3.3 Avenues for future research

The main results in this Chapter is that P-ETF investors are less willing to trade lottery-like stocks. The former have been identified using the approach of Kumar (2009). However, other lottery-like stock measures have been used in the literature, such as the maximum daily return over the past one month (MAX) (Bali et al., 2011), the retail trading proportion (RTP)(Han and Kumar, 2013), the modified MAX (Hung and Yang, 2018), or the institutional ownership indicator(IO) (Tsai et al., 2021). It could have been insightful to investigate the sensitivity of our findings regarding stock gambling, when opting for these alternative lottery-like stock measures.

3.4 Conclusions

Bhattacharya et al. (2017) show that retail investors trade P-ETFs poorly, mainly because they choose bad ETFs and trade them at bad times. We do not question this broad study, which mixed all types of P-ETFs, from the most standard to the most exotic ETFs. We instead complement it by focusing on retail investors who potentially follow the traditional portfolio management ‘wisdom’ of following a simple and diversified investment strategy. Retail investors can easily apply this strategy by holding passive ETFs invested in stocks (P-ETFs).

We use a sample of 14,134 Belgian investors over the January 2003-March 2012 period, with two types of data: trading records and surveys. Using propensity score probabilities estimated in a logistic regression model, we match our target group of P-ETF retail investors to a reference group of investors who only hold stocks, leading to two similar groups of similar size. Controlling for all of the key investor characteristics (including sociodemographics, financial knowledge, financial experience, level of education or portfolio value), we reach the following conclusions.

First, retail investors who hold P-ETFs trade differently than the reference group. Retail investors who hold P-ETFs have a larger portfolio size, a lower turnover, and keep their assets for a longer period of time than the reference group of retail investors who hold individual stocks only. Retail investors in P-ETFs grasp the contribution of passive instruments to long-term investing.

Second, we cluster P-ETF retail investors into four groups according to the weights of P-ETFs in their aggregate portfolios and show that retail investors who hold P-ETFs do not behave homogeneously. Heavy P-ETF investors, i.e., holding more than 75% of their aggregate portfolio in P-ETFs, have a smaller number of individual securities in the portfolios and lower turnover.

Third, P-ETF retail investors are more prudent as regards stock gambling. We identify lottery-type stocks at the monthly frequency among all of the stocks traded in our

sample using two lottery-type stock preference measures. Controlling for all of the key individual characteristics again, we find strong evidence that retail investors who invest in P-ETFs have a lower propensity to gamble by investing in lottery-type stocks. Among holders of P-ETFs, the retail investors who are least likely to hold lottery-like stocks are those who invested the most in P-ETFs.

There is overall strong evidence that P-ETF investors show 'better' trading behaviour than investors of individual stocks from the standpoint of modern portfolio theory.

Chapter 4

Do stock retail investors show better portfolio performance when they hold passive ETFs?

Chapter Abstract

We investigate the portfolio performance of retail investors who combine stocks and passive exchange traded funds (P-ETFs) by relying on both proprietary trading records and survey data. We use propensity score matching to control for all the key investor characteristics and better identify the contribution of holding P-ETFs in retail portfolios. We find that heavy P-ETFs investors trade more passively, while light P-ETF investors trade as actively as investors who hold individual stocks only. The level of total and systematic risks are lower in portfolios held by P-ETF investors. The risk-adjusted performance remains negative for all retail investors, irrespective of their exposure to P-ETFs. Nevertheless, retail investors who hold P-ETFs generate higher risk-adjusted returns than those who trade individual stocks only.

Keywords: ETFs, Retail Investors, Passive Investing, Core-Satellite.

JEL classification: G11, G40, G53

4.1 Introduction

Although the Efficient Market Hypothesis (EMH) is considered to be a cornerstone of modern finance, it is still hotly debated in the finance literature. In its strongest form, the EMH assumes that all past and current information in a market, whether public or private, is fully reflected in market prices (Malkiel and Fama, 1970). It is therefore impossible to “beat the market” since the price of a stock follows a random walk (Samuelson, 1965; Van Horne and Parker, 1967). As a consequence of the randomness of financial prices, proponents of the EMH have concluded that investors are better off investing in passive Exchange-Traded Funds (P-ETFs) which aims to replicate the performance of broadly diversified indexes. The popularity of passive investment strategies has not stopped gaining ground since the 1970’s. For example, Malkiel (2003) supports the superiority of passive investment strategies in all markets against active strategies.

The rise of P-ETFs in the mid of 90’s has mitigated the under-diversification issue in retail portfolios, which has been widely documented in the literature (e.g., Blume and Friend, 1975; Campbell, 2006; Goetzmann and Kumar, 2008; Grinblatt et al., 2012; Barber and Odean, 2013). In spite of this greater popularity, retail investors still consider individual stocks to be their most straightforward and obvious choice of investment. This is explained in the literature by the fact that investing in ETFs requires a higher level of financial knowledge and experience. For instance, Müller and Weber (2010), Enete et al. (2018) and D’Hondt et al. (2022) find that ETF users have a higher (subjective or objective) financial knowledge, compared to non-users of ETFs.

Retail investors also trade differently when they hold P-ETFs. D’Hondt et al. (2021) show that they have a higher portfolio size, a lower turnover, and keep their assets for a longer period of time than the control group of retail investors who hold individual stocks only. P-ETF retail investors are also more conservative when it comes to stock gambling, and those among them who follow a core-satellite approach are least likely to hold lottery-like stocks. Da Dalt et al. (2019) provide additional evidence that households

adopt contrarian behaviors when they trade ETFs. Finally, D'Hondt et al. (2022) find that the most active users of passive ETFs hold a lower number of stocks and modify the composition of their portfolio less extensively, pointing to a substitution effect between stocks and P-ETFs.

According to Oehler and Wanger (2020), plain-vanilla ETFs can boost the portfolio performance of households, especially when their portfolios are under-diversified. ETFs are found to be generally suitable to optimize the performance of households' portfolios under consideration of multiple relevant asset classes. In contrast, Bhattacharya et al. (2017) show that retail investors do not benefit when they hold ETFs in their portfolios, because of poor ETF timing as well as poor ETF selection. However, poor trading performance is also true when investing in actively-managed costly mutual funds (Beshears et al., 2018; Frazzini and Lamont, 2008) and the underperformance of retail investors in the stock markets has been widely documented (Odean, 1999; Barber and Odean, 2000; Grinblatt and Keloharju, 2009; Ben-David and Hirshleifer, 2012). This can be explained by overconfidence (Barber and Odean, 2000), overtrading (Barber and Odean, 2001), the disposition effect (Shefrin and Statman, 1985), low investment talent, or IQ (Grinblatt et al., 2012).

To the best of our knowledge, the literature has not answered the question as to whether retail investors benefit from investing in *both* stocks and P-ETFs. On the one hand, retail investors could limit the risk of underperformance by diversifying their portfolio and holding P-ETFs. On the other hand, retail investors could still try to achieve positive abnormal returns by actively managing a few stocks only.

The main contribution of our study is therefore to test whether retail investors who combine stocks and passive ETFs in their portfolios achieve higher performance than the reference group of retail investors who exclusively invest in individual stocks. We use propensity score matching to control for confounding factors and select the most suitable investors in the reference group, allowing us to better measure the contribution of P-ETFs to retail portfolio performance. We also take into consideration the actual,

observable weight of P-ETFs in the aggregate portfolio and hence avoid using the simple binary, ‘all-or-nothing’ classification method when determining whether retail investors benefit from P-ETFs. This allows us to split the sample of P-ETF users into two groups: light P-ETF investors with less than 50% of their aggregate portfolio invested in P-ETFs, and heavy P-ETF investors with at least 50%. In addition, we estimate portfolio performance through different risk-adjusted return measures at the aggregate portfolio level and for each security type separately (P-ETFs and stocks).

Our main findings can be summarized as follow. First, we find that heavy P-ETF investors adopt more passive investing behaviours when managing their portfolio. This group of investors show lower trading activity, such as lower number of trades and lower turnover, in comparison to investors who trade individual stocks exclusively. There is interestingly no statistical significant difference between light P-ETF investors and individual stocks investors regarding their trading behavior.

Second, we use panel regressions over the period spanning four years, and find that portfolio performance, as measured by gross and net excess returns, is positive and significantly higher for light P-ETF investors with respect to individual stock investors, whereas there is no statistical significance for heavy P-ETF investors.

Third, both P-ETF investor groups show lower total and systematic risks and higher risk-adjusted portfolio performance in comparison to individual stock investors. This holds true when we split the aggregate portfolio into stocks and P-ETFs. When we compare light and heavy P-ETF investors, we find no significant difference between their respective aggregate portfolio, whether from the perspective of total risk, systematic risk, or risk-adjusted performance.

Finally, we focus on two risk-adjusted performance measures, i.e., the α and the Sharpe ratio. Using cross-sectional regressions, we confirm that retail investors who invest in P-ETFs reach significantly higher risk-adjusted return in comparison to retail investors who invest in stocks only. However, all risk-adjusted performance measures are still negative, meaning that P-ETF investors perform “less bad” than individual stock investors once

their exposure to risk factors are accounted for.

The remainder of the paper is organized as follows. Section 4.2 describes our data and our sample. We report our empirical results in section 4.3. We conclude in Section 4.4.

4.2 Data and sample

4.2.1 Data

Our data come from an online Belgian brokerage house. They are made of two datasets. The first dataset provides information about the trading activity of 13,129 retail investors between January 2008 and March 2012. For each investor, we have detailed trading records. We count 463 retail investors trading 99 different passive ETFs. They account for 3.53% of the retail investors in our sample.

The second dataset provides matched individual data that we classify as either sociodemographic or survey-based. Socio-demographic variables include age, gender, education and spoken language. The survey-based data are subjective investor characteristics collected by the brokerage house within the context of the European MiFID regulation. In short, this piece of regulation has made it compulsory for investment firms to collect specific information about their retail clients' needs and preferences. Accordingly, investment firms operating in the EU are required to submit questionnaires (that are then referred to as "MiFID tests") to their clients. Specifically, two tests have emerged: (1) the Appropriateness test (hereafter the A-test), and (2) the Suitability test (hereafter the S-test). Investors who ask for order execution on "complex" instruments have to fulfill the A-test. This test aims at ensuring that the investor has the necessary experience and knowledge to understand the risks involved in these "complex" financial instruments. Investors who ask for financial advice and/or portfolio management services have to fulfill the S-test, which aims at assessing their level of knowledge and experience, their investment objectives as well as their financial capacity.

For the purpose of this study, we make a distinction between "subjective" variables, which are based on the aforementioned A-test and S-test, and "objective" variables, which characterize the trading activity of retail investors. Table 4.1 includes a brief description of variables and investors characteristics used in the paper.

4.2.2 The Sample

The goal of our study is to test whether retail investors who invest in stocks show a better performance when they also hold passive ETFs. We therefore define two groups of investors. The target group includes 463 investors who hold both stocks and P-ETFs (TG hereafter). The second group includes 13,129 investors who invest in stocks only (SOG hereafter). To reduce the confounding biases and have a similar number of investors in both groups, we use the propensity score matching approach (PSM hereafter). More precisely, we match both groups by using propensity score probabilities estimated with a logistic regression model¹ The PSM approach leads to the selection of 444 investors in our reference group (RG hereafter). Figure 4.1 displays the evolution of the number of investors per month.

Table 4.2 shows the averages, standard deviations, and differences in means between the TG, SOG and RG for a large set of variables related to socio-demographics, financial literacy (subjective variables) and portfolio value. In the last column of Table 4.2, we clearly see that the RG is appropriately constituted since all the differences in the discriminant variables between the TG and the SOG are no longer significant. The TG and RG groups are therefore similar regarding sociodemographics, subjective variables, and portfolio value.

¹The PSM approach used is explained in details in our Appendix 6.3.1.

Table 4.1: Brief description of variables and investor characteristics.

Variable	Description	Source
Panel A: Socio-demographic variables		
Age	Difference between 2012 and the year of birth.	Self-reported.
Gender	Dummy variable equal to one if the investor is a male.	Self-reported.
Higher education (Hig-edu)	Dummy variable equal to one if the investor holds a university degree or equivalent.	Self-reported.
Dutch speaking (Dut-spe)	Dummy variable equal to one if the investor who chooses Dutch as the main language on the online brokerage trading platform.	Self-reported.
French speaking (Fre-spe)	Dummy variable equal to one if the investor who chooses French as the main language on the online brokerage trading platform.	Self-reported.
English speaking (Eng-spe)	Dummy variable equal to one if the investor who chooses English as the main language on the online brokerage trading platform.	Self-reported.
Panel B: Subjective variables		
Knowledge of financial markets (Kno-fin-mar)	Investor's self-assessment regarding his or her knowledge of financial markets (score between 0 and 3).	Self-reported (MIFID Tests).
Knowledge of 'complex' instruments (Kno-com-ins)	Investor's self-assessment regarding his or her knowledge of 'complex' instruments (score between 0 and 3).	Self-reported (MIFID Tests).
Experience with 'complex' instruments (Exp-com-ins)	Investor's self-assessment regarding his or her experience with complex instruments (score between 0 and 18).	Self-reported (MIFID Tests).
Awareness of the losses of 'complex' instruments (Awa-com-ins)	Investor's self-assessment regarding his or her awareness of the losses of 'complex' instruments (score between 0 and 9).	Self-reported (MIFID Tests).
Appetite for information (App-inf)	Dummy variable equal to 1 if the investor has asked for an access to the information tool on stocks and has completed the S-test, 0 otherwise.	Self-reported (MIFID Test).
Panel C: Trades-based variables		
Number of trades	Number of trades executed over the sample period.	Transaction trades records.
Trading experience	Difference between the last and the first trading dates, expressed in number of months.	Transaction trades records.
Trade duration	Average number of days between two consecutive trades.	Transaction trades records.
Number of different securities traded	Number of different securities traded during the whole period.	Transaction trades records.
Number of trading days	Number of different trading days during the whole period.	Transaction trades records.
Turnover (Turn)	Average of the absolute values of all of the purchases and sales in a particular month divided by the average of the portfolio values at the beginning and the end of this particular month.	Transaction trades records.
Panel D: Portfolio-based variables		
Portfolio size (Pae-siz)	Average number of securities held in the end-of-month portfolio.	Transaction trades records.
Portfolio value (Por-val)	Monthly average end-of-month portfolio market value in euros.	Transaction trades records.

Table 4.2: Descriptive statistics - before and after the propensity score matching

		TG n = 463 (1)		SOG n = 13,129 (2)		RG n = 444 (3)		t-test	
		Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Diff-1 (1)-(2)	Diff-2 (1)-(3)
Panel A: Socio-demographics									
Age (2012)	Years	46.78	12.65	47.39	13.15	47.02	13.26	-0.618	-0.245
Gender	Dummy=1 if male	0.877	0.329	0.854	0.352	0.856	0.352	0.022	-0.006
Higher education	Dummy=1 if university	0.758	0.428	0.646	0.478	0.786	0.411	0.112***	-0.028
Dutch-speaking	Dummy=1 if Dutch	0.512	0.500	0.544	0.498	0.487	0.500	-0.032	0.025
French-speaking	Dummy=1 if French	0.391	0.488	0.410	0.492	0.405	0.492	-0.019	-0.015
English-speaking	Dummy=1 if English	0.097	0.297	0.047	0.212	0.108	0.311	0.050***	-0.011
Panel B: Subjective variables (Score Min-Max)									
Knowledge of financial markets	(score 0-3)	1.296	0.888	1.080	0.921	1.320	0.929	0.216***	-0.024
Knowledge of 'complex' instruments	(score 0-18)	4.827	5.024	4.153	4.812	4.410	4.931	0.674***	0.417
Experience with 'complex' instruments	(score 0-18)	3.620	4.771	3.254	4.498	3.475	4.657	0.366*	0.145
Awareness of the losses of 'complex' instruments	(score:0-9)	7.019	3.385	6.595	3.689	7.083	3.335	0.425***	-0.064
Appetite for information	Dummy	0.536	0.499	0.433	0.496	0.556	0.497	0.103***	-0.021
Panel C: Portfolio-based variables									
Portfolio value (in eur)	(in €)	32,431.0	137,933	27,080.5	126,714	34,364.6	89,604.4	5,350.5	1,933.6

The table reports the cross-sectional means, standard deviations and differences in means between the target group of investors who hold both stocks and P-ETFs (TG), the group of stock-only investors (SOG) before selection by the PSM approach, and the reference group of stock-only investors (RG) after selection by the PSM approach. Panel A includes socio-demographics. 'Age' is determined as the difference between 2012 and the year of birth. 'Gender' is a dummy variable equal to one if the investor is a male. 'Higher education' refers to the proportion of investors who declare that they hold a university degree or equivalent. 'Dutch-speaking', 'French-speaking' and 'English-speaking' refer to the proportion of investors who choose Dutch, French, and English respectively as the main language on the online brokerage trading platform. Panel B includes subjective variables and refers to the A-test. 'Knowledge of financial markets' refers to one specific question where investors have to self-assess their knowledge of financial markets on a scale of four levels, wherein Level 0 is associated with a basic knowledge while Level 3 refers to an experienced investor 'who manages any aspect of the financial markets'. For 'Knowledge of "complex" instruments', 'Experience with "complex" instruments' and 'Awareness of the losses with "complex" instruments', the score indicates the investor's self-assessment regarding his/her own abilities and skills. For example, a score of 18 out of 18 for the Knowledge of "complex" instruments means that the investor considers himself/herself as an expert in the field. Conversely, a score of 0 (out of 18) indicates that the investor declares no knowledge about "complex" instruments. 'Appetite for information' is a dummy variable with a value of 1 if the investor has asked for an access to the information tool on stocks and has completed the S-test and 0 otherwise. Panel C includes 'Portfolio value' which is the monthly average end-of-month portfolio market value in €. *, **, *** indicate that the difference is statistically significant at the level of 10%, 5% or 1%, respectively.

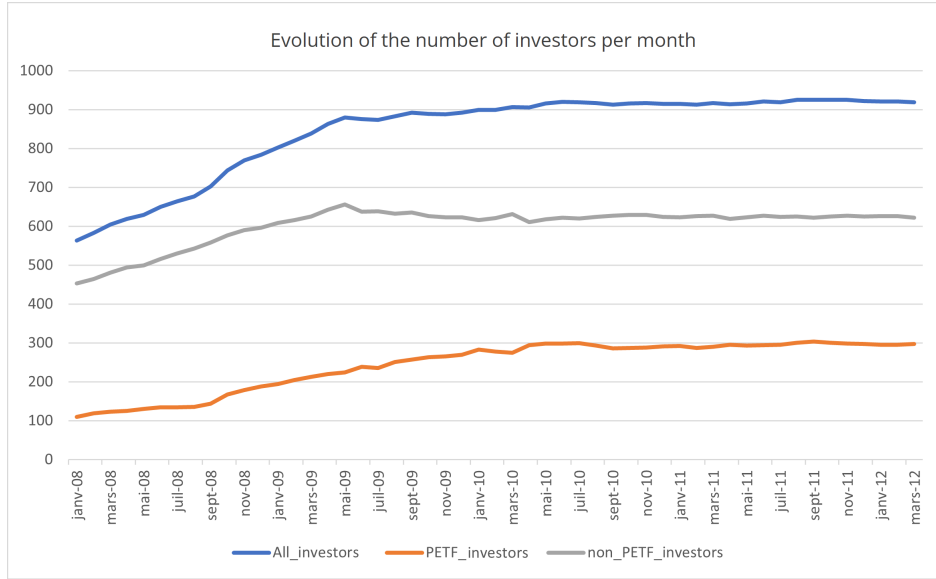


Figure 4.1: Evolution of the number of investors per month.

This figure shows the evolution of the number of investors per month from January 2008 to March 2012, depending if they trade passive ETFs or not. The horizontal axis refers to the date, while the vertical axis refers to the number of investors. The blue line refers to the evolution of the number of all investors, the grey line refers to the evolution of number of non P-ETF investors, and the orange line refers to the evolution of the number of P-ETF investors.

4.3 Empirical results

To better estimate the contribution of passive ETFs to portfolio performance, we further split the TG in two subgroups: ‘Light’ P-ETF users (LTG hereafter) and ‘heavy’ P-ETF users (HTG hereafter). The HTG includes retail investors who invest at least 50% of the aggregate portfolio in P-EFTS, while the weight is less than 50% in the LTG. The goal is to test whether retail portfolio performance is sensitive to the degree of allocation in P-ETFs. Figure 4.2 displays the histogram of investors’ distribution according to the weight of P-ETFs in the portfolio.

4.3.1 Trading activeness

Table 4.3 reports the cross-sectional medians for a large set of variables and compares their distribution between the target groups (LTG and HTG) and the reference group

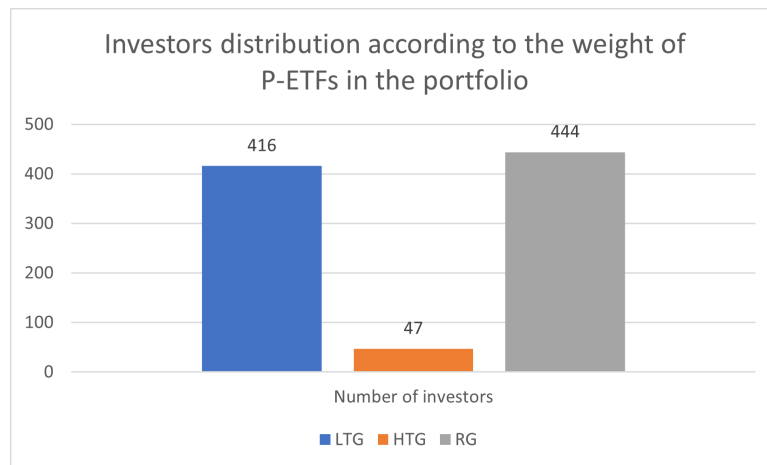


Figure 4.2: Histogram of TG investors' distribution.

This figure shows the distribution of investors according to the weight of P-ETFs in their aggregate portfolio.

(RG) over the full sample period. We use the Wilcoxon rank-sum test to compare the distributions and report the corresponding p-values in the last three columns.²

²The null hypothesis of the non-parametric rank-sum Wilcoxon test is usually taken as equal medians. If we reject the null that the two populations have the same distribution with the same median, one distribution is shifted to the left or to the right of the other distribution. In this case, we have evidence that the medians of the two populations differ.

Table 4.3: Comparisons between TG and RG investors at the aggregate portfolio level.

Weight of P-ETF in aggregate portfolio	LTG]0% – 50%[n=416	HTG [50% – 100%] n=47	RG 0% n=444	Wilcoxon rank-sum median test		
	Median (1)	Median (2)	Median (3)	p-value (1)-(2)	p-value (1)-(3)	p-value (2)-(3)
Panel A: Trades-based variables						
Number of trades	22.000	9.000	20.000	< .000	0.053	< .000
Turnover	0.045	0.028	0.051	< .000	0.070	< .000
Trading experience	35.000	16.000	33.000	< .000	0.387	< .000
Trade duration	43.296	85.231	37.865	< .000	0.275	< .000
Number of different securities traded	10.000	4.000	8.000	< .000	< .000	< .000
Number of trading days	15.500	4.000	16.000	< .000	0.991	< .000
Panel B: Portfolio-based variables						
Portfolio size	4.727	1.760	4.265	< .000	0.006	< .000
Portfolio value (in eur)	6,955.43	9,795.59	10,779.06	0.279	< .000	0.609

The table reports the cross-sectional median for the two target groups (LTG and HTG) as well the reference group (RG). LTG includes investors who hold both stocks and P-ETFs, with less than 50% of the aggregate portfolio invested in P-ETFs. HTG includes investors who hold both stocks and P-ETFs, with at least 50% of the aggregate portfolio invested in P-ETFs. RG includes investors who only hold stocks but match the profiles of investors included in LTG and HTG. The respective p-values of Wilcoxon rank-sum median tests are reported in the last three columns. ‘Number of trades’ is the number of trades executed across all securities. ‘Turnover’ is the monthly average turnover. It is calculated as in Hoffmann et al. (2013), i.e. average of the absolute values of all purchases and sales in a particular month divided by the average of the portfolio values at the beginning and the end of this particular month. ‘Trading experience’ is computed as the difference between the last trade date and the first trade date available in the sample. It is expressed in number of months. ‘Trade duration’. ‘Number of different securities traded’ is the number of different securities traded during the whole trading period. ‘Number of trading days’ is the number of different days securities are traded over the sample period. ‘Portfolio size’ is the monthly average number of securities held in portfolio. ‘Portfolio value’ is the monthly average portfolio market value.

Trading activity measures are reported in Panel A of Table 4.3. Light P-ETF users (LTG) show similar levels of trading activity to the stock-only investors (RG). The differences between the two groups are economically marginal, even in the case of the *Number of different securities traded* for which the difference is statistically significant at 1%.

This does not hold true for heavy P-ETF users (HTG) who behave very differently. They trade much more passively than the two other groups (LTG and RG). All the trading activity measures are significantly lower for this group of investors, both from an economic and statistical perspectives.

This result suggests that the higher the portfolio weight in P-ETFs, the higher the disposition towards passive portfolio management. This is in line with the assumption that retail investors with at least 50% of their aggregate portfolio in P-ETFs, use these instru-

ments as the core in their portfolio in order to ensure a sufficient level of diversification, capture the return of the market, and avoid lagging behind the crowd by a wide margin. Interestingly, Bouchey and Pritamani (2017) find that the optimal allocation to the core portfolio should typically be greater than 50% for taxable investors with moderate levels of risk aversion. These proportions should be even higher when investors are highly risk averse or expect a limited outperformance from their portfolio satellite typically invested in individual stocks. According to Amenc et al. (2004), ETFs are a natural vehicle for implementing a core-satellite investment approach, as they may increase the return of the portfolio while keeping under control its relative risk, i.e., the risk of deviating from the portfolio benchmark.

Panel B of Table 4.3 reports the median portfolio size and value across retail investors over the sample period. Portfolio size corresponds to the monthly average number of securities held in the portfolio. It is significantly lower for heavy P-ETF users (HTG), implying that their portfolio size is around three times smaller than those held by LTG investors. A higher allocation in P-ETFs offers HTG investors sufficient diversification for them to hold fewer individual securities.

HTG and RG retail investors have a similar median portfolio value (in euros) while it is around 30% lower for LTG retail investors. Combining a lower portfolio value and a higher portfolio size, we can conclude that LTG retail investors invest much less in each security they hold, i.e., around 1480 euros versus 5567 for HTG investors. This does *not* mean HTG investors are less diversified since HTG investors invest more in P-ETFs which are diversified instruments by construction.³

³In Tables 6.14 and 6.15 in Appendix 6.3.2, we run the same regression analyses on the two components of the portfolio separately, i.e., the P-ETF and stock components, and come to similar conclusions. We also observe the same results for the aggregate portfolio when we use the mean as a measure of comparison between groups. Results are reported in Table 6.16 in Appendix 6.3.2 as well.

4.3.2 Portfolio Performance

In this section we estimate the portfolio performance of the three groups of retail investors included in our analysis over 51 months, from January 2008 to March 2012. These investors are split in the RG, LTG, and HTG groups, as explained in the previous section.

We first need to estimate the monthly aggregate portfolio returns. We use the modified Dietz (1968) method, which is close to the money weighted rate of return. We also assume that all the purchases (and sales) executed in a given month take place on the first (and last) day of the month. This gives:

$$Return_{i,t}^{gross} = \frac{(EMV_t - EMV_{t-1}P_t + S_t)}{(EMV_{t-1} + P_t)} \quad (4.1)$$

where $Return_{i,t}^{gross}$ is the portfolio gross return for investor i at month t ; EMV_t is the end-of-month portfolio value at month t ; EMV_{t-1} is the end-of-month portfolio value at month $t - 1$; P_t and S_t are the aggregate monetary values of all purchases and sales executed during month t .

We compute the corresponding net monthly returns by subtracting from the numerator the aggregate monetary value paid on transaction costs during month, i.e., $Costs_t$. This gives:

$$Return_{i,t}^{net} = \frac{(EMV_t - EMV_{t-1}P_t + S_t - Costs_t)}{(EMV_{t-1} + P_t)} \quad (4.2)$$

We use equations 4.1 and 4.2 to compute gross and net returns for P-ETFs and individual stocks separately in the LTG and HTG portfolios.

To ensure that the results of the performance computed based on returns using equations 4.1 and 4.2 are not driven by any outliers, we winsorize the excess gross and net returns

at the 0.5 and 99.5 percentiles, which implies that we set all observations that fall outside this interval to the 0.5 and 99.5 percentile values respectively.

Adjusting for risk using panel data

Returns must also be adjusted for risk and there are many ways to account for it. In this section, we include risk factors in panel regressions to examine whether investing in P-ETFs allows stock investors to improve their portfolio performance. The model is:

$$XSR_{i,t} = \beta_0 + \beta_1 * LTG_i + \beta_2 * HTG_i + \beta_3 * Crisis_t + \beta_4 * LTG_i * Crisis_t + \beta_5 * HTG_i * Crisis_t + \beta_6 * RF_t + \beta_7 * SD_i + \beta_8 * SV_i + \beta_9 * OV_i + \epsilon_{i,t} \quad (4.3)$$

wherein the dependent variable is $XSR_{i,t}$, i.e., the aggregate portfolio gross (or net) return of investor's i in month t , as defined in equations 4.1 and 4.2, in excess to the risk-free rate. LTG_i is a dummy variable set to 1 if the average weight of P-ETFs in investor i 's aggregate portfolio over sample period is between]0%;50%[, 0 otherwise. HTG_i is a dummy variable set to 1 if the average weight of P-ETFs in investor i 's aggregate portfolio over sample period is in the interval [50%;100%], 0 otherwise. $Crisis_t$ is a dummy variable set to 1 for every month t between April 2008 and March 2009, 0 otherwise.⁴

To control for risk factors, we include the Fama-French-Carhart risk factors for the European market in the RF_t vector. This vector includes the usual four risk factors, namely *Market risk premium*, *Size*, *Book-to-market*, and *Momentum*.⁵

To control for individual characteristics, we include SD_i as a vector of sociodemograph-

⁴For this dummy we use the same period for the financial crisis as in Hoffmann et al. (2013). As robustness check, we create an alternative for the variable "Crisis" as the "% of trades during financial crisis 2008" for each investors i , where the empirical results remain consistent regarding our variables of interest, and the results are reported in Table 6.18 in the Appendix.

⁵Market factors for the European market are provided by Eurofidai (<http://www.eurofidai.org>).

ics, which includes *age*, *gender*, the *level of education* and the *spoken language* of investor i . The second vector, SV_i , includes subjective variables which are based on investor i 's answers to the A-test. It includes *Knowledge of financial markets*, *Knowledge of 'complex' instruments*, *Experience with 'complex' instruments*, and *Awareness of the losses of 'complex' instruments*. The third vector, OV_i , corresponds to objective variables and is based on trading records. It includes the *Portfolio market value*, *Portfolio size*, *Number of trades*, *Trading experience*, *Trade duration* and *Turnover* by retail investor i .⁶

We cluster standard errors by month for this panel data regressions, as the goal is to handle any potential concerns related to cross-sectional correlation (Seasholes and Zhu (2010)).

Table 4.4 reports the results for six panel specifications. The dependent variable is the *Excess gross return* of the aggregate portfolio for models (1), (2) and (3), and its corresponding *Excess net return* for models (4), (5), and (6).

As indicated in Panel A of Table 4.4, the aggregate portfolio return of retail investors is improved when retail investors invest in both stocks and P-ETFs. All the coefficient estimates of the LTG and HTG variables are positive in all six models. However, statistical significance is much stronger for the LTG investors since the coefficient estimates are always statistically significant at 5% in all models. This would indicate that if retail investors seek to maximize their portfolio performance, they should not load up P-ETFs for more than 50% of their portfolio value.

Nevertheless, the intercept in each model specification remains negative and statistically significant at 1% level, even when the LTG or HTG coefficient estimates are added up. Holding P-ETFs helps reduce the negative β_0 , but does not make it positive. This is consistent with the findings in the literature that retail investors are unable to achieve positive abnormal returns on average. In other words, the negative β_0 means that the

⁶We do not include all the objective variables presented in previous sections in our regressions, to avoid any potential issues related to multicollinearity. For example, this is the case between *Number of trades* and *Number of trading days* or between *Number of trading days* and *Number of different securities traded* (Cf. Table 6.17 in Appendix 6.3.3).

Table 4.4: Explaining excess returns in TG investors' aggregate portfolio.

Dependent variable	Gross excess return			Net excess return		
	Estimate x 100 (1)	Estimate x 100 (2)	Estimate x 100 (3)	Estimate x 100 (4)	Estimate x 100 (5)	Estimate x 100 (6)
Explanatory variables						
Panel A : Variables of interest						
Intercept	-0.817***	-1.439**	-1.600***	-0.929***	-1.685***	-1.812***
LTG (P-ETFs weight [0%-50%[)	0.628***	0.649***	0.474**	0.618***	0.641***	0.466**
HTG (P-ETFs weight [50%-100%[)	0.622*	0.571*	0.501	0.686*	0.628*	0.539
Crisis			-0.119			-0.157
LTG*Crisis			0.723			0.700
HTG*Crisis			0.0839			0.857
Panel B : Market factors						
Risk premium	95.477***	95.522***	97.121***	95.905***	95.959***	97.418***
SMB	28.002***	28.024***	29.762***	27.982***	27.920***	29.509***
HML	28.472***	28.434***	29.268***	28.257***	28.212***	29.021***
MOM	-19.036***	-19.045***	-19.130***	-18.519***	-18.521***	-18.634***
Panel C: Socio-demographic variables						
Age		0.009	0.008		0.012**	0.010**
Gender		-0.095	-0.062		-0.105	-0.072
Higher education		0.173	0.222		0.920	0.276 *
Dutch-speaking		0.123	0.085		0.132	0.091
English-speaking		0.505*	0.507*		0.555	0.538*
Panel D : Subjective variables						
Knowledge of financial markets			-0.100			-0.083
Knowledge of 'complex' instruments			-0.003			-0.004
Experience with 'complex' instruments			0.023			0.024
Awareness of the losses of 'complex' instruments			-0.011			-0.017
Appetite for information			-0.217**			-0.250***
Panel E : Objective variables						
Number of trades			-0.001			-0.002**
Trading Experience			0.008*			0.007*
Trade duration			-0.000			-0.000
Turnover			-0.012***			-0.13***
Portfolio size			0.037**			0.044***
Portfolio value (in eur)			0.000			0.000
N	39,254	39,254	37,160	39,254	39,254	37,160
R ²	0.3803	0.3806	0.3788	0.3789	0.3794	0.3777

This table reports the results of panel regressions where the dependent variable is the gross excess return in models (1), (2) and (3) and net excess return in models (4), (5) and (6). Panel A includes the two explanatory variables of interest, LTG and HTG which are dummy variables equal 1 if investor i is in the target group of light and heavy P-ETF users respectively, 0 otherwise. $Crisis_t$ is a dummy variable set to 1 for every month t between April 2008 and March 2009, 0 otherwise. For this dummy we use the same period for the financial crisis as in Hoffmann et al. (2013). Panel B includes four market factors: 'Risk premium', 'SMB', 'HML' and 'MOM', which are the market, the size, the book-to-market and the momentum factors, respectively, for the European market which are provided by Eurofidai. Panel C includes Socio-demographics. 'Age' is determined as the difference between 2012 and the year of birth. 'Gender' is a dummy variable equal to one if the investor is a male. 'Higher education' refers to the proportion of investors who declare that they hold a university degree or equivalent. 'Dutch-speaking', 'French-speaking' and 'English-speaking' refer to the proportion of investors who choose Dutch, French, and English respectively as the main language on the online brokerage trading platform. Panel D includes subjective variables and refers to the A-test. 'Knowledge of financial markets' refers to one specific question where investors have to self-assess their knowledge of financial markets on a scale of four levels, wherein Level 0 is associated with a basic knowledge while Level 3 refers to an experienced investor 'who manages any aspect of the financial markets'. For 'Knowledge of "complex" instruments', 'Experience with "complex" instruments' and 'Awareness of the losses with "complex" instruments', the score indicates the investor's self-assessment regarding his/her own abilities and skills. For example, a score of 18 out of 18 for the Knowledge of "complex" instruments means that the investor considers himself/herself as an expert in the field. Conversely, a score of 0 (out of 18) indicates that the investor declares no knowledge about "complex" instruments. 'Appetite for information' is dummy variable with a value of 1 if the investor has asked for an access to the information tool on stocks and has completed the S-test and 0 otherwise. Panel E includes objective variables: 'Number of trades' is the number of trades executed across all securities. 'Turnover' is the monthly average turnover. It is calculated as in Hoffmann et al. (2013), i.e. average of the absolute values of all purchases and sales in a particular month divided by the average of the portfolio values at the beginning and the end of this particular month. 'Trading experience' is computed as the difference between the last trade date and the first trade date available in the sample. It is expressed in number of months. 'Trade duration'. 'Number of different securities traded' is the number of different securities traded during the whole trading period. 'Number of trading days'. 'Portfolio size' is the monthly average number of stocks held in portfolio. 'Portfolio value' is the monthly average portfolio market value. *, **, *** indicate that the difference is statistically significant at the level of 10%, 5% or 1%, respectively.

average (or median) retail investor cannot “beat” the market through stock picking or market timing.

Panel B in Table 4.4 shows that all risk factors are statistically significant at the 1% significance level in all models. With respect to the level of systematic risk exposure, retail investors load up what a traditional stock index would require them to bear since their estimated market beta is very close to 1. The three other risk factors suggest that investors in our sample hold portfolios that are tilted towards small caps, value stocks, and contrarian strategies.

When it comes to socio-demographic variables, Panel C in Table 4.4 shows that English-speaking investors have statistically higher performance in comparison to French-speaking investors. All else equal, there is also some statistical evidence that net excess returns are also positively correlated with the level of education and age.

In Panel D, *Appetite for information* is the only statistically significant variable. This dummy characterizes investors who ask for access to an information tool on stocks after completing the suitability test. We conjecture that the negative sign of its coefficient estimate could be explained by the tendency of these investors to overtrade. Access to this tool may motivate them to react to stock news excessively.⁷

Finally, *Trading experience Portfolio size* in Panel E are positively correlated with portfolio performance, all else equal, while this is the opposite for *Number of trades Turnover*. These results are perfectly consistent with the findings in the literature regarding trading and portfolio performance by individual investors (Beshears et al. (2018) among others).

Portfolio performance must also be studied by considering the asset categories that retail investors hold in their portfolio. The LTG and HTG investors hold two categories of securities, namely individual stocks and ETFs. As shown in Table 4.4, they outperform

⁷This is in accordance with the findings of Nofsinger (2001) who shows that investors trade more around news releases, especially around earnings announcement and dividend payout dates. He also finds that the length of the news article is an important factor to motivate trading. In the same vein, Kaniel et al. (2012) show that individual have intense trading before and after earnings announcement events.

the stock-only investors whose performance is estimated by the model intercept. However, we still need to determine whether the outperformance by P-ETF users (included in LTG and HTG) comes from the fact they invest in P-ETFs, individual stocks, or both. To answer that question, Tables 4.5 and 4.6 rely on the same model specifications than above, but the performance of each category of securities held in LTG and HTG investors' portfolios, is considered separately. Table 4.5 investigates the P-ETF component while Table 4.6 considers the stock component.

Table 4.5 shows that the outperformance of LTG and HTG investors is much weaker when we zoom in on the P-ETF component of their portfolio. For example, statistical significance for both LTG and HTG dummies disappears when the full set of control variables is considered. This result may be very well explained by the fact that P-ETFs are not held in their portfolio to achieve abnormal returns, but rather to replicate the return of a broad market segment.

The β_0 remains negative and statistically significant at 1% level, irrespective of the groups of investors. The LTG and HTG retail investors still generate negative abnormal returns as they fail to show strong selection or market timing abilities. This was already pointed out by Bhattacharya et al. (2017). However, P-ETF users still perform better than the stock-only investors. To rephrase Bhattacharya et al. (2017), abusing P-ETFs is detrimental to retail investors, but to a lesser extent than abusing stocks.

In Table 4.6, we disregard the P-ETFs held by TG investors and focus on the performance of stocks only. The two LTG and HTG dummies therefore capture the performance of stocks held by light and heavy P-ETF users. Contrary to Table 4.5, the LTG and HTG investors clearly outperform RG investors since the two dummies are statistically significant at 1%. This implies that investors who invest in both P-ETFs and stocks, hold better performing stocks than the stock-only investors regarding the net(& gross) excess return. Among the P-ETF users, the best performing stocks are held by the HTG retail investors, i.e., the heavy users of P-ETFs, as indicated by the highest HTG dummy coefficient estimate. In a core-satellite approach where the core is invested in

Table 4.5: Explaining excess returns in the P-ETF component of TG investors' aggregate portfolio.

Dependent variable	Gross excess return			Net excess return		
	Estimate x 100 (1)	Estimate x 100 (2)	Estimate x 100 (3)	Estimate x 100 (4)	Estimate x 100 (5)	Estimate x 100 (6)
Explanatory variables						
Panel A : Variables of interest						
Intercept	-0.905***	-1.349**	-1.431***	-1.007***	-1.539***	-1.601***
LTG (P-ETFs weight [0%-50%[)	0.745*	0.753*	0.334	0.764*	0.774*	0.349
HTG (P-ETFs weight [50%-100%[)	0.736*	0.708*	0.522	0.834*	0.775*	0.575
Crisis			-0.346			-0.367
LTG*Crisis			2.321			2.267
HTG*Crisis			1.739			1.739
Panel B : Market factors						
Risk premium	96.529***	96.599***	98.243***	96.824***	96.904***	98.435***
SMB	22.351***	22.393***	24.778***	22.097***	22.144***	24.403***
HML	18.890**	18.846**	19.560**	18.649**	18.598**	19.294**
MOM	-16.878**	-16.855**	-16.470**	-16.490**	-16.465**	-16.125**
Panel C: Socio-demographic variables						
Age		0.008*	0.006		0.010**	0.007*
Gender		-0.119	-0.135		-0.127	-0.142
Higher education		0.084	0.137		0.109	0.164
Dutch-speaking		0.041	-0.003		0.049	0.006
English-speaking		0.531**	0.487*		0.571**	0.514**
Panel D : Subjective variables						
Knowledge of financial markets			-0.027			-0.018
Knowledge of 'complex' instruments			-0.010			-0.010
Experience with 'complex' instruments			0.011			0.012
Awareness of the losses of 'complex' instruments			-0.013			-0.015
Appetite for information			-0.237**			-0.266**
Panel E : Objective variables						
Number of trades			-0.002*			-0.002**
Trading Experience			0.008*			0.007
Trade duration			0.001			0.001
Turnover			-0.013**			-0.014**
Portfolio size			0.048***			0.054***
Portfolio value (in eur)			-0.000			0.000
N	31,683	31,683	29,663	31,683	31,863	29,663
R ²	0.3613	0.3617	0.3570	0.3619	0.3623	0.3578

This table reports the results of panel regressions where the dependent variable is the gross excess return in models (1), (2) and (3) and net excess return in models (4), (5) and (6). Panel A includes the two explanatory variables of interest, LTG and HTG which are dummy variables equal 1 if investor i is in group light and heavy P-ETF users respectively, 0 otherwise. $Crisis_t$ is a dummy variable set to 1 for every month t between April 2008 and March 2009, 0 otherwise. For this dummy we use the same period for the financial crisis as in Hoffmann et al. (2013). Panel B includes four market factors: 'Risk premium', 'SMB', 'HML' and 'MOM', which are the market, the size, the book-to-market and the momentum factors, respectively, for the European market which are provided by Eurofidi. Panel C includes Socio-demographics. 'Age' is determined as the difference between 2012 and the year of birth. 'Gender' is a dummy variable equal to one if the investor is a male. 'Higher education' refers to the proportion of investors who declare that they hold a university degree or equivalent. 'Dutch-speaking', 'French-speaking' and 'English-speaking' refer to the proportion of investors who choose Dutch, French, and English respectively as the main language on the online brokerage trading platform. Panel D includes subjective variables and refers to the A-test. 'Knowledge of financial markets' refers to one specific question where investors have to self-assess their knowledge of financial markets on a scale of four levels, wherein Level 0 is associated with a basic knowledge while Level 3 refers to an experienced investor 'who manages any aspect of the financial markets'. For 'Knowledge of "complex" instruments', 'Experience with "complex" instruments' and 'Awareness of the losses with "complex" instruments', the score indicates the investor's self-assessment regarding his/her own abilities and skills. For example, a score of 18 out of 18 for the Knowledge of "complex" instruments means that the investor considers himself/herself as an expert in the field. Conversely, a score of 0 (out of 18) indicates that the investor declares no knowledge about "complex" instruments. 'Appetite for information' is dummy variable with a value of 1 if the investor has asked for an access to the information tool on stocks and has completed the S-test and 0 otherwise. Panel E includes objective variables: 'Number of trades' is the number of trades executed across all securities. 'Turnover' is the monthly average turnover. It is calculated as in Hoffmann et al. (2013), i.e. average of the absolute values of all purchases and sales in a particular month divided by the average of the portfolio values at the beginning and the end of this particular month. 'Trading experience' is computed as the difference between the last trade date and the first trade date available in the sample. It is expressed in number of months. 'Trade duration'. 'Number of different securities traded' is the number of different securities traded during the whole trading period. 'Number of trading days'. 'Portfolio size' is the monthly average number of stocks held in portfolio. 'Portfolio value' is the monthly average portfolio market value. *, **, *** indicate that the difference is statistically significant at the level of 10%, 5% or 1%, respectively.

P-ETFs and the satellite in stocks, this would be precisely the goal: Investors load up on passive ETFs to get exposed to market risk and return, while they aim to realize abnormal returns by holding individual stocks. Regarding the other explanatory factors, the empirical results remain unchanged and lead to the same conclusions as in Tables 4.4 and 4.5.

Overall, Tables 4.4, 4.5, and 4.6 show that the two portfolio components held by the TG investors deliver the expected performance at the portfolio level. First, P-ETFs are held in portfolios with the goal of replicating the performance of markets, not to beat them. It should therefore come as no surprise that the component invested in P-ETFs do not exhibit abnormal returns irrespective of the percentage invested in them (Table 4.5). Second, the satellite component in already well-diversified portfolios such as those held by TG investors precisely aims to provide abnormal positive returns. Table 4.6 indicates that TG investors do a better job at investing in better performing stocks than RG investors regarding the net (& gross) excess return, but they still fail to obtain positive alphas in their stock portfolio component. This is the case in all the six models reported in Table 4.6. For example, the sum of the intercept and the HTG or dummy coefficient is still negative in model (3). This is also the case in Table 4.4 in the aggregate portfolio. Consequently, both RG and TG retail investors are not unable to generate positive abnormal returns, i.e., returns that are uncorrelated with portfolio risk factors.

Adjusting for risk using individual time series and cross-sectional medians

Another way to estimate portfolio performance on a risk-adjusted basis is to use each investor's time series of monthly excess returns over the whole sample period, and then compute cross-sectional medians for each of the three groups of investors discussed above, i.e., RG, LTG, and HTG investors. Contrary to the panel data models used in the previous sections where *average* marginal effects are computed, the performance analysis below relies on the use of the *median* which is a more informative measure of central tendency when distributions are skewed or contain outliers.

Table 4.6: Explaining excess returns in the individual stock component of TG investors' aggregate portfolio.

Dependent variable	Gross excess return			Net excess return		
	Estimate x 100 (1)	Estimate x 100 (2)	Estimate x 100 (3)	Estimate x 100 (4)	Estimate x 100 (5)	Estimate x 100 (6)
Explanatory variables						
Panel A : Variables of interest						
Intercept	-0.773***	-1.497**	-1.714***	-0.885***	-1.750***	-1.932***
LTG (P-ETFs weight [0%-50%[)	0.626***	0.648***	0.503***	0.614***	0.639***	0.491***
HTG (P-ETFs weight [50%-100%[)	0.728***	0.665***	0.749***	0.779***	0.708***	0.769***
Crisis			0.040			-0.013
LTG*Crisis			0.571			0.558
HTG*Crisis			0.088			0.097
Panel B : Market factors						
Risk premium	95.220***	95.265***	97.54***	95.616***	95.670***	97.778***
SMB	31.914***	31.935***	33.576***	31.825***	31.852***	33.348***
HML	33.242***	33.203***	33.822***	33.038***	32.991***	33.574***
MOM	-21.375***	-21.378***	-21.516***	-20.864***	-20.867***	-21.051***
Panel C: Socio-demographic variables						
Age		0.010	0.010*		0.012*	0.012**
Gender		-0.111	-0.076		-0.123	-0.089
Higher education		0.237	0.280*		0.287*	0.338**
Dutch-speaking		0.171	0.131		0.182	0.141
English-speaking		0.527	0.515		0.582*	0.550
Panel D : Subjective variables						
Knowledge of financial markets			-0.121			-0.101
Knowledge of 'complex' instruments			0.006			0.005
Experience with 'complex' instruments			0.018			0.019
Awareness of the losses of 'complex' instruments			-0.006			-0.012
Appetite for information			-0.224**			-0.258**
Panel E : Objective variables						
Number of trades			-0.000			-0.002**
Trading Experience			0.001*			0.008
Trade duration			-0.000			-0.000
Turnover			-0.012**			-0.013***
Portfolio size			0.034*			0.041**
Portfolio value (in eur)			0.000			0.000
N	38,734	38,734	36,799	38,734	38,734	36,799
R ²	0.3615	0.3619	0.3635	0.3596	0.3601	0.3619

This table reports the results of panel regressions where the dependent variable is the gross excess return in models (1), (2) and (3) and net excess return in models (4), (5) and (6). Panel A includes the two explanatory variables of interest, LTG and HTG which are dummy variables equal 1 if investor i is in group light and heavy P-ETF users respectively, 0 otherwise. $Crisis_t$ is a dummy variable set to 1 for every month t between April 2008 and March 2009, 0 otherwise. For this dummy we use the same period for the financial crisis as in Hoffmann et al. (2013). Panel B includes four market factors: 'Risk premium', 'SMB', 'HML' and 'MOM', which are the market, the size, the book-to-market and the momentum factors, respectively, for the European market which are provided by Eurofidai. Panel C includes Socio-demographics. 'Age' is determined as the difference between 2012 and the year of birth. 'Gender' is a dummy variable equal to one if the investor is a male. 'Higher education' refers to the proportion of investors who declare that they hold a university degree or equivalent. 'Dutch-speaking', 'French-speaking' and 'English-speaking' refer to the proportion of investors who choose Dutch, French, and English respectively as the main language on the online brokerage trading platform. Panel D includes subjective variables and refers to the A-test. 'Knowledge of financial markets' refers to one specific question where investors have to self-assess their knowledge of financial markets on a scale of four levels, wherein Level 0 is associated with a basic knowledge while Level 3 refers to an experienced investor 'who manages any aspect of the financial markets'. For 'Knowledge of "complex" instruments', 'Experience with "complex" instruments' and 'Awareness of the losses with "complex" instruments', the score indicates the investor's self-assessment regarding his/her own abilities and skills. For example, a score of 18 out of 18 for the Knowledge of "complex" instruments means that the investor considers himself/herself as an expert in the field. Conversely, a score of 0 (out of 18) indicates that the investor declares no knowledge about "complex" instruments. 'Appetite for information' is dummy variable with a value of 1 if the investor has asked for an access to the information tool on stocks and has completed the S-test and 0 otherwise. Panel E includes objective variables: 'Number of trades' is the number of trades executed across all securities. 'Turnover' is the monthly average turnover. It is calculated as in Hoffmann et al. (2013), i.e. average of the absolute values of all purchases and sales in a particular month divided by the average of the portfolio values at the beginning and the end of this particular month. 'Trading experience' is computed as the difference between the last trade date and the first trade date available in the sample. It is expressed in number of months. 'Trade duration'. 'Number of different securities traded' is the number of different securities traded during the whole trading period. 'Number of trading days'. 'Portfolio size' is the monthly average number of stocks held in portfolio. 'Portfolio value' is the monthly average portfolio market value. *, **, *** indicate that the difference is statistically significant at the level of 10%, 5% or 1%, respectively.

Table 4.7 reports medians for different performance measures of returns and risk at the aggregate portfolio level across investors belonging to the same groups (RG, LTG, and HTG).⁸ We use Wilcoxon rank-sum tests to compare samples distribution. Their p-value are reported in the last three columns.

Table 4.7: Comparison between TG and RG investors at the aggregate portfolio level.

Weight of P-ETF in aggregate portfolio	LTG]0% – 50%[n=416	HTG [50% – 100%] n=47	RG 0% n=444	Wilcoxon rank-sum test		
	Median (1)	Median (2)	Median (3)	P-value (1)-(2)	P-value (1)-(3)	P-value (2)-(3)
Panel A : Return						
Arithmetic net excess return (annualized)	-0.049	-0.064	-0.115	0.525	< .000	0.001
Arithmetic gross excess return (annualized)	-0.037	-0.061	-0.105	0.252	< .000	0.001
Panel B : Volatility						
Volatility (annualized)	0.261	0.219	0.405	0.003	< .000	< .000
Downside Deviation (annualized)	0.182	0.151	0.324	0.006	< .000	< .000
Panel C : One-factor model coefficients						
One-factor Alpha	-0.005	-0.005	-0.010	0.979	< .000	< .000
One-factor Beta	0.993	0.939	1.160	0.307	< .000	0.001
Panel D : Four-factor model coefficients						
Four-factor Alpha	-0.003	-0.004	-0.006	0.378	< .000	0.174
Four-factor Beta (Market premium)	0.936	0.871	0.977	0.467	0.012	0.090
Four-factor Beta (Size)	0.173	-0.023	0.309	< .000	< .000	< .000
Four-factor Beta (HML)	0.145	0.105	0.211	0.521	0.179	0.205
Four-factor Beta (MOM)	-0.063	-0.007	-0.172	0.163	0.005	0.011
Panel E : Risk-adjusted performance measures						
Sharpe Ratio	-0.195	-0.297	-0.342	0.257	< .000	0.082
Treynor Ratio (one-factor beta)	-0.051	-0.071	-0.099	0.613	< .000	0.006
Treynor Ratio (four-factor beta)	-0.047	-0.088	-0.104	0.423	< .000	0.012
Sortino Ratio	-0.254	-0.429	-0.406	0.207	< .000	0.293
Information Ratio	-0.208	-0.550	-0.432	0.012	< .000	0.763

The table reports the cross-sectional median for TG groups (aggregate portfolios) and RG (Stocks portfolio), on a per investor basis over the sample period.

In Panel A, we report the medians across each investor's aggregate portfolio monthly gross (or net) return in excess to the risk-free rate, as explained in equations 4.1 and 4.2. Our results show that both LTG and HTG investors have statistically higher arithmetic excess net and gross return relative to RG investors. However, the annualized return are negative for all three groups of investors in our sample, which confirms our previous

⁸Appendix 6.3.5 includes Tables 6.19 and 6.20 which report the same analysis for the two components of TG investors' portfolios separately, i.e., the P-ETF and individual stock portfolio components.

findings in the panel data analysis.

Panel B displays annualized volatility (total risk) and downside deviation. Results show that TG investors' aggregate portfolio risk is significantly lower than for RG investors. This holds true for both risk measures. This can be explained by the more concentrated portfolios that RG investors hold, with a median of four stocks in their portfolio, contrary to five securities for LTG and HTG investors, including P-ETFs which are diversified by definition. HTG investors are those who display the lowest levels of volatility and downside risk. They indeed invest a greater percentage of their portfolios in diversified P-ETFs. However, had their individual stocks been extremely volatile, the ranking between the three groups would have been different. This outcome demonstrates that the satellite of individual stocks that HTG investors hold does not counterbalance the benefit of keeping risk under control through diversified P-ETFs.

In panel C and D of Table 4.7, we estimate two standard asset pricing models to adjust for risk. We first control for the CAPM market risk factor and run the following regression:

$$XSR_{i,t}^{net} = \alpha_i + \beta_i * MKTRF_t + \epsilon_{i,t}. \quad (4.4)$$

wherein the dependent variable is $XSR_{i,t}^{net}$, the aggregate portfolio monthly gross (or net) return of investor i in excess to the risk-free rate; and $MKTRF_t$ is the return of the market risk factor for the European market computed at month t by Eurofidai.

We then extend the analysis and add three risk factors, i.e., Fama and French (1993)'s size and value risk factors as well Carhart (1997)'s momentum risk factor. The model becomes:

$$XSR_{i,t}^{net} = \alpha_i^* + \beta_{1i} * MKTRF_t + \beta_{2i} * SMB_t + \beta_{3i} * HML_t + \beta_{4i} * MOM_t + \epsilon_{i,t} \quad (4.5)$$

wherein SMB_t , HML_t and MOM_t are respectively the return of the size, value and momentum risk factors for the European market computed at month t by Eurofidai.

We are therefore able to estimate each investor's α_i and α_i^* parameters, i.e., the one-factor alpha and four-factor alpha respectively, as well as their risk factor beta parameters.

In Panel C, we observe that the one-factor alpha medians for both groups of TG investors is statistically higher than the median computed for RG investors. In the four-factor model, the difference remains significant between LTG and RG investors. Overall, P-ETFs investors achieve higher abnormal returns than stock-only investors, keeping in mind that the alphas remains negative for all groups.

The market risk premium coefficient estimates are close to one in all groups. Still, the level of systematic risk is statistically lower for TG investors, implying that P-ETF investors hold more defensive stocks than stock-only investors. The size (SMB) factor coefficients are also statistically different between the TG and RG groups. HTG hold securities tilted towards large caps, while it is the opposite for LTG and RG investors, with the latter being most exposed to small caps. Interestingly, the HML beta coefficients show no statistical difference among the three groups as their portfolio returns are all more correlated with value stock returns. Finally, the momentum risk factor coefficient estimates indicate that all three groups are more oriented towards contrarian stocks, with a significant difference between TG and RG investors again.

Panel E in Table 4.7 reports the cross-sectional medians for three risk-adjusted portfolio performance measures, i.e., the Sharpe, Treynor, Sortino and information ratios. For each measure, the numerator corresponds to the net excess return. The Sharpe ratio controls for total risk; the Treynor ratio controls for systematic risk estimated in both the one-factor and four-factor models; the Sortino ratio takes downside risk into consideration; and finally, the information ratio takes into account the tracking error, i.e., the divergence between the portfolio and the benchmark (market portfolio). Clearly, risk-adjusted performance between LTG and HTG is similar, irrespective of the selected measure. However, stock-only (RG) investors (again) underperform from risk-adjusted performance. Their performance is statistically lower in all cases, except for their Sortino and Information ratios are equivalent to the HTG group. Still, all risk-adjusted measures

remain negative, which means that retail investors underperform the market portfolio in risk-adjusted terms.

Explaining risk-adjusted performance using cross-sectional data

To gain more insight into the drivers of retail investors' risk-adjusted aggregate portfolio performance, we run regressions with the one-factor alpha (α_i), four-factor alpha (α_i^*), and Sharpe ratio as dependent variable in turn.

The cross-sectional data model given in 4.6 uses each investors' risk-adjusted performance estimated over the whole sample and regress it on the drivers documented in the previous sections. The model is:

$$RAM_i = \beta_0 + \beta_1 * LTG_i + \beta_2 * HTG_i + \beta_3 * SD_i + \beta_4 * SV_i + \beta_5 * OV_i + \epsilon_i \quad (4.6)$$

wherein the dependent variable is RAM_i , i.e., the aggregate portfolio one-factor, four-factor alpha and Sharpe ratio of investor's i in turn; LTG_i is a dummy variable set to 1 if the average weight of P-ETFs hold by investor i over sample period is in the interval]0%;50%[of his aggregate portfolio, 0 otherwise; HTG_i is a dummy variable set to 1 if the average weight of P-ETFs hold by investor i over sample period is in the interval [50%;100%] of his aggregate portfolio, 0 otherwise. To control for individual characteristics, we include SD_i as a vector of sociodemographics, which includes *age*, *gender*, the *level of education* and the *spoken language* of investor i . The second vector, SV_i , includes subjective variables which are based on investor i 's answers to the A-test. It includes *Knowledge of financial markets*, *Knowledge of 'complex' instruments*, *Experience with 'complex' instruments*, and *Awareness of the losses of 'complex' instruments*. The third vector, OV_i , corresponds to objective variables and is based on trading records. It includes the *Portfolio market value*, *Portfolio size*, *Number of trades*, *Trading experience*, *Trade duration* and the *Turnover* by retail investor i .

Table 4.8 reports the OLS regressions of model 4.6, where the dependent variables are

the *one-factor alpha* in models (1) and (2), *four-factor alpha* in models (3) and (4), and *Sharpe ratio* in models (5) and (6). Models (1), (3), and (5) include the OV_i vector of variables, while models (2), (4), and (6) include them.

Table 4.8 confirms that the risk-adjusted return in the aggregate portfolio is significantly higher for P-ETF investors than for RG investors, except in models (3) and (4) where the performance of RG investors is equivalent to the performance of HTG investors.

Regarding sociodemographics, *Higher education* has a significant impact on the risk-adjusted performance of the aggregate portfolio across the three groups of investors. *English-speaking* is also positive and statistically significant in the one-factor alpha and Sharpe ratio models.

Among the subjective variables, the only significant outcome is obtained for *Knowledge of financial markets* which negatively impacts the risk-adjusted performance portfolio of retail investors as measured by the one-factor alpha and the Sharpe ratio. We conjecture that *Knowledge of financial markets* would capture the well-documented bias of overconfidence, as it refers to one specific question where investors have to *self-assess* their knowledge of financial markets on a scale of four levels, wherein Level 3 refers to an experienced investor 'who manages any aspect of the financial markets'.

Table 4.8: Explaining risk-adjusted performance using cross-sectional data.

Dependent variable	One-factor alpha		Four-factor alpha		Sharpe ratio	
	Estimate (1)	Estimate (2)	Estimate (3)	Estimate (4)	Estimate (5)	Estimate (6)
Explanatory variables						
Panel A : Variables of interest						
Intercept	-0.029***	0.032***	-0.016**	-0.015*	-0.346***	-0.390***
LTG (P-ETF weight]0%-50%])	0.013***	0.012***	0.006**	0.006*	0.203***	0.204***
HTG (P-ETF weight [50%-100%])	0.012***	0.014***	0.005	0.005	0.150**	0.234***
Panel B: Socio-demographic variables						
Age	0.000*	0.000	-0.000	-0.000	-0.000	-0.000
Gender	-0.002	-0.002	0.004	0.004	-0.039	-0.059
Higher education	0.006***	0.009***	0.007*	0.010**	0.083*	0.094**
Dutch-speaking	-0.001	-0.000	-0.002	-0.002	0.026	0.006
English-speaking	0.006*	0.007*	-0.001	-0.001	0.106*	0.131**
Panel C : Subjective variables						
Knowledge of financial markets	-0.004***	-0.005***	-0.002	-0.003	-0.044*	-0.058**
Knowledge of 'complex' instruments	0.000	-0.000	0.001	0.001	-0.006	-0.006
Experience with 'complex' instruments	0.000	0.001	-0.001	-0.001	0.006	0.007
Awareness of the losses of 'complex' instruments	-0.000	-0.000	-0.001	-0.001	-0.001	-0.003
Appetite for information	-0.000	-0.002	-0.003	-0.001	-0.010	-0.028
Panel D : Objective variables						
Number of trades		-0.000*		-0.000		-0.000
Trading experience		0.000***		0.005		0.003*
Trade duration		0.000		0.000		0.000
Turnover		-0.000		-0.000		-0.003*
Portfolio size		0.001***		0.000		0.008**
Portfolio value (in eur)		0.000		0.000		-0.000**
N	907	907	907	907	907	907
R ²	0.059	0.108	0.011	0.022	0.048	0.077

The table reports the cross-sectional regressions where the dependent variables are *One-factor alpha* for models (1) and (2), *Four-factor alpha* for models (3) and (4) and *Sharpe-ratio* for models (5) and (6). Panel A includes the two explanatory variables of interest, LTG and HTG which are dummy variables equal 1 if investor i is in group light and heavy P-ETF users respectively, 0 otherwise. Panel B includes Socio-demographics: 'Age' is determined as the difference between 2012 and the year of birth. 'Gender' is a dummy variable equal to one if the investor is a male. 'Higher education' refers to the proportion of investors who declare that they hold a university degree or equivalent. 'Dutch-speaking', 'French-speaking' and 'English-speaking' refer to the proportion of investors who choose Dutch, French, and English respectively as the main language on the online brokerage trading platform. Panel C includes subjective variables and refers to the A-test. 'Knowledge of financial markets' refers to one specific question where investors have to self-assess their knowledge of financial markets on a scale of four levels, wherein Level 0 is associated with a basic knowledge while Level 3 refers to an experienced investor 'who manages any aspect of the financial markets'. For 'Knowledge of "complex" instruments', 'Experience with "complex" instruments' and 'Awareness of the losses with "complex" instruments', the score indicates the investor's self-assessment regarding his/her own abilities and skills. For example, a score of 18 out of 18 for the Knowledge of "complex" instruments means that the investor considers himself/herself as an expert in the field. Conversely, a score of 0 (out of 18) indicates that the investor declares no knowledge about "complex" instruments. 'Appetite for information' is dummy variable with a value of 1 if the investor has asked for an access to the information tool on stocks and has completed the S-test and 0 otherwise. Panel D includes objective variables: 'Number of trades' is the number of trades executed across all securities. 'Turnover' is the monthly average turnover. It is calculated as in Hoffmann et al. (2013), i.e. average of the absolute values of all purchases and sales in a particular month divided by the average of the portfolio values at the beginning and the end of this particular month. 'Trading experience' is computed as the difference between the last trade date and the first trade date available in the sample. It is expressed in number of months. 'Trade duration'. 'Number of different securities traded' is the number of different securities traded during the whole trading period. 'Number of trading days'. 'Portfolio size' is the monthly average number of stocks held in portfolio. 'Portfolio value' is the monthly average portfolio market value. *, **, *** indicate that the difference is statistically significant at the level of 10%, 5% or 1%, respectively.

Finally, as for the objective variables, *Trading experience* and *Portfolio size* (which captures the level of diversification) show significant and positive impact on the one-factor alpha and Sharpe ratio, while *Turnover* and *Portfolio value* have significant negative impact only on the Sharpe ratio. These results are in line with the literature on retail investing.

4.3.3 Avenues for future research

Regarding avenues for future research, the present Chapter mainly explores the performance of P-ETF retail investors. There is nevertheless other points of this topic that still need to be explored. A relevant question is related to the representativeness of the time period covered in our analysis, i.e., the 2008-2012 time period. The conclusions of our empirical analyses arguably depends on the length of the time window and the inclusion of the crisis, although we did our best to control for its impact. A sensitivity and replication analysis on a different and longer period of time would be welcome.

4.4 Conclusion

Whether retail investors benefit from investing in *both* stocks and P-ETFs has remained an open question in the literature. By holding both types of securities, retail investors would limit the risk of underperformance by holding P-ETFs and hence diversifying their portfolio, while at the same time trying to achieve positive abnormal returns by actively managing individual stocks.

To test whether retail investors who combine stocks and passive ETFs in their portfolios achieve higher performance, we use propensity score matching to compare them to the most suitable, stock-only investors. This technique allows us to control for confounding factors and better measure the contribution of P-ETFs to retail portfolio performance. We also take into consideration the actual, observable weight of P-ETFs in the aggregate

portfolio and hence avoid using the simple binary, ‘all-or-nothing’ classification method when determining whether retail investors benefit from P-ETFs. This allows us to split the sample of P-ETF users into two groups: light P-ETF investors with less than 50% of their aggregate portfolio invested in P-ETFs, and heavy P-ETF investors with at least 50%. In addition, we estimate portfolio performance through different risk-adjusted return measures at the aggregate portfolio level and for each security type separately (P-ETFs and stocks).

We show that retail investors who mix P-ETFs and individual stocks, achieve higher performance, even after adjusting for risk. This holds true when we zoom in on the stock component of their portfolios. Both groups, light and heavy P-ETF investors, show statistically higher return, lower total risk, lower systematic risk, and higher risk-adjusted return relative to individual stocks only investors. In addition, heavy P-ETFs show significant lower trading activeness than light P-ETFs and stock-only investors.

However, being ‘less bad’ than stock-only investors is not good enough. The risk-adjusted performance measures remain negative even for the P-ETF investors and irrespective of the weight of P-ETFs in their portfolio. For example, the alpha remains negative and statistically significant at 1% level for all groups of investors. Consequently, the P-ETF retail investors still generate negative abnormal returns as they fail to show strong selection or market timing abilities.

It remains that P-ETF users still perform better than the stock-only investors. To rephrase Bhattacharya et al. (2017), abusing P-ETFs is detrimental to retail investors, but to a lesser extent than abusing stocks.

Chapter 5

General Conclusion

“In my view, for most people, the best thing to do is owning the S&P 500 index fund, [...] there are huge amounts of money people pay for advice they really don’t need. If you bet on America and sustain that position for decades, you’d do far better than buying Treasury securities, or far better than following people who tell you in what to invest”.
(Buffett, 2020)

Retail investors are more than ever left to their own fate, in a world marked by huge and rapid rise in new technologies and new financial instruments. Exchange Traded Funds provide retail investors with an easy access to many investment styles, markets, asset classes and sectors at a low cost and a low level of risk over long periods of time. According to the literature passive ETFs and index funds are the most suitable financial vehicles for the so-called "dumb money", i.e. retail investors, thanks to the multitude of advantages that Ferri (2010) summarizes as follows " *Today, actively managed funds aren’t needed to gain broad diversification in an asset class. Index funds and ETFs perform that function much more efficiently. The costs are lower, diversification is*

broader, the transparency of fund holdings is superior, and the tax benefit from lower turnover helps investors whose accounts are subject to taxation."

In this perspective, this doctoral dissertation aims at studying the relationship between retail investors and passive ETFs. Indeed, our research complements previous studies related to the trading behavior of retail investors focusing on individual stocks or mutual funds. The literature has already identified several anomalies regarding individual stock trading (Subrahmanyam, 2008), as well as two major anomalies regarding mutual funds trading, which consists in buying mutual funds with high fees and chasing returns (Bailey et al., 2011). This research investigates three fundamental questions related to the use of passive Exchange Traded Funds by retail investors. The first question focuses on the profiling of passive ETF investors. The second question focuses on the way retail investors trade passive ETFs. The third question focuses on how well do retail investors perform when they hold passive ETFs in their portfolio.

5.1 Main results and contributions

In light of the acceleration of the process of democratization of passive Exchange Traded Funds among retail investors the second chapter puts the emphasis on the determining factors that lead retail investors to hold passive ETFs in their portfolio, therefore following the recommendation of a large proportion of academics. The analysis shows that both the likelihood and magnitude of retail investors buying P-ETFs are driven by higher education, longer trading experience, higher financial literacy and a long investment horizon. These investors suffer less from overconfidence and from local bias.

In Chapter II, we provide evidence that the P-ETF investors are sophisticated investors, and this result is all the more interesting since it is somewhat opposite to what one

might expect, which is retail investors who have limited resources, i.e. limited capital, time, or skills, are those who invest the most in passive ETFs. These findings provide direct evidence that a great part of retail investors may have not yet understood the benefits and the full potential of this financial instrument or may not have heard of its existence yet.

The goal of Chapter III is to better understand the trading behavior of passive ETF retail investors, by controlling for all the key investors characteristics related to the sociodemographic factors, trading activity, and subjective individual attributes. We examine whether retail investors are able to grasp the contribution of passive investment vehicles to both diversification and long-term investing.

In Chapter III we also argue that P-ETF retail investors trade differently. Indeed, they show a better understanding of the diversification concept, adopt a longer term passive investment strategy, hold a larger portfolio and have a lower turnover than the reference group of retail investors who hold individual stocks only.

We also provide additional evidence regarding the sophistication of passive ETF investors. In fact, P-ETF retail investors show a conservative attitude regarding stock gambling, and those among them who invest the most in P-ETFs are the least likely to hold lottery-like stocks.

Chapter IV investigates the impact of passive ETFs on the retail investors portfolio performance. The objective is to test whether retail investors who combine stocks and passive ETFs in their portfolio achieve a higher performance than those who hold only individual stocks. Taking into consideration the observable weight of P-ETFs in the aggregate portfolio, we investigate portfolio performance through several risk-adjusted return measures at the aggregate portfolio level and for each security type separately.

In Chapter IV we show that the investors who mix P-ETFs and individual stocks achieve

a higher performance, even after adjusting for risk. These results remain true when we focus on the stock part of the portfolio. All P-ETF investors, light and heavy users, exhibit a statistically higher return, a lower total risk, a lower systematic risk and a higher adjusted return relative to individual stock-only investors. We also find that heavy P-ETF investors show a significantly lower trading activity than light P-ETF stock-only investors.

Finally, the fact that P-ETFs investors are 'less bad' than stock-only investors, is not good enough. The risk-adjusted performance measures remain negative even for the P-ETF investors and irrespective of the weight of P-ETFs in their portfolio, confirming what is well documented in the literature regarding the poor portfolio performance of retail investors.

5.2 Managerial implications and limitations

This dissertation does not cover every aspect related to retail investors and passive Exchange Traded Funds. However, we are able to contribute in several ways to the literature on household finance, and our findings have considerable managerial implications for market participants.

First, our results are very interesting for *retail investors*. To begin with, for most retail investors who are opting for trading based exclusively on individual stocks, the transaction costs and the behavioral mistakes are likely prohibitive. Our findings suggest that passive Exchange Traded Funds are relevant financial instruments for retail investors, thanks to their numerous advantages meant to help them achieve their financial objectives. Next, it is well documented in the literature that there exists a large heterogeneity among retail investors regarding their behavior and performance (Barber and Odean,

2013). However, our results suggest that the investors who report higher levels of financial literacy and experience tend to make wiser investment decisions in terms of both portfolio management and trading performance. Hence, it is essential for this type of investors to keep improving their own financial literacy and knowledge, because it is a paramount driver in the enhancement of their trading decisions and behavior.

Second, our doctoral dissertation provides insightful findings to *the academic community*. As the majority of studies focus on retail investors who are trading individual stocks and mutual funds, our dissertation, among other related papers, participate in building a new dimension of research that involves both passive Exchange Traded Funds and the behavior of retail investors.

Third, our doctoral dissertation delivers implications for *banks and financial services providers*. It is important for these institutions to offer the best possible advice for their customers to ensure best outcomes, based on the investor protection framework set out in MiFID II which aims at ensuring that investment firms act in the best interest of their clients. Our findings show that mainly sophisticated investors invest in and benefit from passive ETFs. Hence, banks and financial services providers could take into consideration our results regarding the profile, behavior and performance when advising passive ETF retail investors, so as to deliver the most suitable services to their clients.

Finally, our results may be interesting to *policy makers and regulators*. Our findings may be meaningful for regulators in understanding the behavior of retail investors, and in the framework of enhancing the protection for retail investors under the existing MiFID legislation, especially when considering that we based our empirical analysis on the informative content available in the MiFID tests. Also, our research is perfect evidence for investment firms and regulators that the information and data collected through MiFID tests are relevant and convenient for future studies.

Despite the fact that this work provides several interesting outcomes, our thesis dissertation has nevertheless some limitations. The first potential limitation is linked to the use of subjective data collected via surveys, which may present some drawbacks. Even within the rigorous analysis of this dissertation, the fact that our models are based on some self-reported data, which are collected in the framework of the MiFID test (appropriateness and suitability tests) may invalidate some of our conclusions, because of the potentially inaccurate responses or misunderstood questions.

A second potential limitation is related to the data used to investigate the research questions, which deserves further scrutiny. Indeed, our three essays are based on data that cover the period from 2003 to 2012 and the behavior of retail investors and the decisions they take are dependant on the general market conditions. Over the period 2003-2012 market faced exceptional conditions marked by very high levels of volatility and uncertainty (Great Financial Crisis in 2007-2009 and European Sovereign Debt Crisis in 2011-2012). As a consequence, a replication of our analyses with another sample of investors or another period of time could grant valuable insights regarding our findings.

Mental accounting has also been addressed from a specific perspective. As indicated by Thaler (1980), mental accounting describes the process by which people keeps goals and moves towards those goals separately from each other. Thaler (1999) also defines mental accounting as the set of cognitive operations used by individuals to organize, evaluate, and keep track of financial activities. Soman and Ahn (2011) underline its critical importance: *"We believe that mental accounting is perhaps one of the most pervasive and fundamental skills found in the human species."* In my dissertation, I follow Barberis and Huang (2001) who confirm that when people do their mental accounting, they engage in narrow framing by paying attention to narrowly defined gains and losses. According to Baker and Nofsinger (2002), the reason for this mechanism is that this

process helps people with their self-control, since that keeping things separately allows better measurement of the progress of each goal. We adopt the approach of Kumar and Lim (2008) and Bailey et al. (2011) by using the degree of clustering in the investors' trades to measure narrow framing. These authors especially identify whether an investor executes trades separately (i.e., one trade at a time) or executes multiple trades simultaneously. Mental accounting could have been estimated in more sophisticated ways, in combination with the prospect theory. For example, Grinblatt and Han (2005) indicate that investors subject to mental accounting and the prospect theory are "risk averse over gambles for some stocks and locally risk loving over gambles for others". Because of this difference in risk attitude, they have a greater tendency to sell stocks that have gone up in value since purchase, generating disposition effect.

Several behavioral biases that are linked to mental accounting are addressed in this dissertation, but through the lens of narrow framing. This latter is a process that helps people self-control according to Baker and Nofsinger (2002), because keeping things separate allows for a better assessment of the progress made for each objective. The research question of Chapter II is related to individual characteristics that may impact the decisions of retail investors to trade passive ETFs. When retail investors choose to invest in P-ETFs, it arguably means that they are ready to sacrifice part of their *control* (or *the illusion of control*) that individual stocks may offer (Barberis and Huang, 2001). For this reason, we have expected a negative marginal effect for the "narrow framing" measure, although we found non significant effect for this variable. In Chapters III and IV, the link to the mental accounting is more subtle but still present in our analysis. As explained in the dissertation, ETFs are financial instruments with their own features and it is implicitly assumed that the set of cognitive operations (or the mental accounting) used by retail investors allows them to organize, evaluate and keep track of P-ETFs differently than for individual stocks. Our results show that P-ETF investors indeed

manage their securities differently than those who invest in individual stocks exclusively. The former also show higher risk-adjusted performance measures, although they fail to beat the market, meaning that retail investors are not yet in a position to exploit the full potential of their own cognitive operations.

Regarding avenues for future research, the three essays presented in this dissertation address three dimensions of the relationship between retail investors and passive ETFs. There is arguably a few other angles that still need to be explored. A very interesting question is related to the portfolio performance of retail investors, who invest exclusively in passive ETFs. The goal is to broaden the understanding of passive ETFs and their functioning during periods of crises. Another essential aspect that can be investigated is the comparison of behavior and the performance of passive ETF retail investors, active ETF investors and mutual fund investors. Such a comprehensive investigation could be very interesting in order to better understand the most suitable financial instrument for retail investors and better guide investing decisions.

The debate will remain lively between those who trade passively in line with the *Efficient Market Hypothesis* of Fama (1960) according to which prices reflect all available information, and those who opt for an active investment strategy. But instead of arguing, they should realize that they need each other. As shown in the *Grossman–Stiglitz Paradox* (Grossman and Stiglitz, 1980), there indeed exists a paradox which requires the presence of active market participants since markets cannot be *informationally* efficient in equilibrium, because new information needs to be reflected in prices. This requires effort for which market participants need to be sufficiently compensated, which would be impossible without passive investors. It is clear that our dissertation stands up for the most fragile market participants, i.e. retail investors, and considers the passive investment strategy as the most suitable way to help them achieve their financial objectives. A few poor discretionary investment decisions can indeed harm investors forever.

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Chapter 6

Appendix

6.1 What drives retail investment in passive Exchange Traded Funds?

Table 6.1: The ten most traded P-ETFs in the sample

ETF	Underlying	Number trades	Volume trades
LYXOR ETF BEL 20	Equity	2,348	11,646,158.95
GOLD BULLION SEC	Commodities	1,607	31,304,732.32
US NAT GAS FD ETF	Commodities	1,015	5,315,626.30
U.S. OIL FUND ETF	Commodities	925	8,357,962.81
ETF BRA IBOVESPA LYX	Equity	890	5,724,898.89
LYXOR ETF CHINA ENT.	Equity	809	11,547,219.10
LYXOR ETF CAC 40	Equity	784	12,794,247.82
LYXOR ETF DJ ES 50	Equity	738	11,870,854.82
ETFS NATURAL GAS	Commodities	599	4,219,940.55
LYXOR ETF MSCI INDIA	Equity	582	5,449,180.23
Other (303 passive ETF)	-	12,079	92,588,179.85
Total		22,376	200,819,001.6

This table reports the underlying assets, the number of trades and the volume of trades (in EUR) of the 10 most traded P-ETFs in the sample.

Table 6.2: Results of the ZINB model of retail investors trading from January 2008

Parameter	Model 1				Model 2				Model 3			
	Logit		Negative Binomial		Logit		Negative Binomial		Logit		Negative Binomial	
	Coefficient	OR	Coefficient	IRR	Coefficient	OR	Coefficient	IRR	Coefficient	OR	Coefficient	IRR
Dependent variable												
Number of P-ETF trades												
Independent variables												
Panel A : Sociodemographic variables												
Gender_male (Dummy)	0.029	1.030	0.139	1.149	0.009	1.009	0.080	1.083	0.014	1.014	0.148	1.159
Age (in Years)	-0.003	0.997	0.018***	1.018	0.004	1.004	0.014***	1.014	0.004	1.004	0.014***	1.014
Higher education (Dummy)	-0.398***	0.671	0.108	1.114	-0.298**	0.742	0.238	1.269	-0.317**	0.728	0.169	1.184
Dutch-speaking (Dummy)	0.032	1.033	0.008	1.008	0.080	1.083	0.019	1.019	0.071	1.074	-0.002	0.998
English-speaking (Dummy)	-0.605**	0.546	0.219	1.245	-0.619**	0.539	0.392	1.480	-0.450*	0.638	0.326	1.385
Panel B : Subjective variables (S-test)												
Financial markets and products knowledge (score 0-7)	-0.166***	0.847	0.186***	1.205	-0.170***	0.843	0.164***	1.178	-0.153***	0.858	0.160***	1.174
Target return (score: 1-5)	0.059	1.060	-0.239***	0.787	0.085	1.088	-0.244***	0.783	0.129**	1.137	-0.215***	0.807
Risk tolerance (score 1-5)	0.181***	1.198	0.186***	1.205	0.182***	1.200	0.138**	1.148	0.166**	1.180	0.121*	1.129
Investment time horizon (score 2-11)	-0.097***	0.908	0.023	1.024	-0.070***	0.932	0.057**	1.058	-0.062***	0.940	0.078***	1.081
Wealth and financial situation (score 0-17)	-0.032*	0.968	-0.002	0.999	-0.020	0.981	-0.005	0.995	-0.017	0.983	-0.009	0.991
Panel C : Objective variables												
Log(Trading experience)					-0.172	0.842	0.278**	1.320	-0.161	0.852	0.412***	1.510
Log(Trade duration)					-0.086	0.917	-0.481***	0.618	-0.092	0.912	-0.530***	0.589
Log(Number of stocks)					-0.617***	0.539	-0.500***	0.607	-0.545***	0.580	-0.424***	0.655
Stock trading intensity (STI)					-0.153	0.859	-0.118	0.889	-0.354*	0.702	-0.188	0.829
Underperformance on stocks (UPS)					-0.072	0.930	0.061	1.062	-0.296**	0.744	-0.067	0.936
Panel D : Behavioral variables												
Overconfidence									0.532**	1.711	0.279	1.322
Narrow framing									0.080	1.083	0.066	1.069
Trade underdiversification									0.061	1.063	0.824***	2.279
Portfolio underdiversification									0.276*	1.318	-0.012	0.988
Local bias ratio									0.862***	2.367	-0.391**	0.676
α (dispersion)	2.78***	16.039			1.86***	6.45			1.70***	5.437		
N	4,762				4,762				4,762			
%(Number of P-ETF trades >0)	13%				13%				13%			
Log likelihood	-3,338.36				-3,255.04				-3,227			
AIC	6,722.71				6,576.09				6,540.95			
BIC	6,871.48				6,789.54				6,819.10			

This table reports the results of three ZINB regressions, with a distinction between the logistic and negative binomial components. The dependent variable is the number of P-ETF trades. Panel A refers to sociodemographics as usual control variables. 'Gender' is a dummy variable equal to one if the investor is a male. 'Age' is determined as the difference between 2012 and the investor's year of birth. 'Higher Education' is a dummy variable set to one for investors with a university degree (or equivalent). 'Dutch-speaking' and 'English-speaking' are both dummies based on the language selected by the investor on the online trading platform. Panel B includes subjective variables (from the S-test). For 'Financial markets and products knowledge', 'Risk tolerance', 'Investment time horizon' and 'Wealth and financial situation', the score reflects the investor's direct self-assessment regarding the item. 'Target return' refers to the annual yield investors expect on their investments, selected on scale of 5 levels, wherein level 1 corresponds to 'a yield without any risk of capital loss' and level 5 to 'the inflation rate + more than 12% per year'. Panel C includes objective variables characterizing trading activity. 'Trading experience' is computed as the difference between the last and the first trading dates, expressed in number of months. 'Trade duration' is computed as the average number of days between two consecutive trades on stocks. 'Number of stocks' is the average number of stocks held in the end-of-month portfolio. 'Stock trading intensity' (STI) is a dummy variable set to one if the investor's monthly portfolio turnover (i.e, the average of the absolute values of all the purchases and sales in a particular month divided by the average of the portfolio values at the beginning and the end of this particular month) is in the upper quartile of the sample and zero otherwise. 'Underperformance on stocks' (UPS) is dummy variable equal to one when the investor's net excess Sharpe ratio on stocks is in the lower quartile of the sample and zero otherwise. Panel D refers to behavioral variables. 'Overconfidence' is a dummy variable set to one if the investor displays both overtrading (STI is set to one) and underperformance (UPS set to one), and zero otherwise. 'Narrow framing' is a dummy variable set to one if the investor's adjusted trade clustering (defined as trade clustering minus mean trade clustering of the peer group) is less than zero, and zero otherwise. 'Trade underdiversification' is a dummy variable set to one if the investor's number of different traded stocks is in the lower quartile, and zero otherwise. 'Portfolio underdiversification' is a dummy variable set to one if the investor's monthly HHI (defined as the sum of squared stock portfolio weights) is in the upper quartile, and zero otherwise. 'Local bias ratio' is computed for any investor as the number of trades executed on stocks issued in home (Belgium) and neighboring countries (France, Netherlands, Germany, and Luxembourg) divided by the total number of trades. 'IRR' is the incidence rate ratio, which is equal to the exponential of the coefficient estimate. 'OR' is the odds ratio, which is equal to the exponential of the coefficient estimate. *, **, *** indicate that the coefficient estimate is statistically significant at 10%, 5% or 1%, respectively.

Table 6.3: Results of Negative Binomial model

Parameter	Model 1		Model 2		Model 3		Model 4	
	Coefficient	IRR	Coefficient	IRR	Coefficient	IRR	Coefficient	IRR
Dependent variable								
Number of P-ETF trades								
Independent variables								
Panel A : Sociodemographic variables								
Gender_male (Dummy)	-0.054	0.947	-0.024	0.976	-0.073	0.930	-0.041	0.960
Age (in Years)	0.007***	1.007	0.009***	1.009	0.008***	1.008	0.009***	1.009
Higher education (Dummy)	0.130**	1.139	0.103**	1.108	0.122**	1.130	0.103**	1.108
Dutch-speaking (Dummy)	0.006	1.006	-0.011	0.989	-0.026	0.974	-0.016	0.984
Panel B : Subjective variables (S-test)								
Financial markets and products knowledge (score 0-7)	0.064***	1.066	0.076***	1.079	0.059***	1.061	0.071***	1.074
Target return (score: 1-5)	-0.121***	0.886	-0.096***	0.908	-0.114***	0.892	-0.103***	0.902
Risk tolerance (score 1-5)	0.057**	1.059	0.036	1.037	0.056***	1.058	0.043*	1.044
Investment time horizon (score 2-11)	0.029***	1.029	0.031***	1.031	0.029***	1.029	0.030***	1.030
Wealth and financial situation (score 0-17)	0.005	1.005	0.002	1.002	0.002	1.002	0.002	1.002
Panel C : Objective variables								
Log(Trading experience)	0.149***	1.161	0.660***	1.935	0.145***	1.156	0.513***	1.670
Log(Trade duration)	-0.458***	0.633	-0.456***	0.634	-0.440***	0.644	-0.448***	0.639
Log(Number of stocks)	-0.311***	0.733	-0.357***	0.700	-0.298***	0.742	-0.335***	0.715
Stock trading intensity (STI)	-0.192**	0.825	-0.169**	0.845	-0.131*	0.877	-0.137*	0.872
Underperformance on stocks (UPS)	0.074	1.077	0.104	1.110	0.083	1.087	0.105	1.111
Panel D : Behavioral variables								
Overconfidence	0.129	1.138	0.042	1.043	0.097	1.102	0.050	1.051
Narrow framing	0.028	1.028	0.012	1.012	0.012	1.012	0.007	1.007
Trade underdiversification	0.620***	1.859	0.620***	1.859	0.579***	1.784	0.601***	1.824
Portfolio underdiversification	-0.113	0.893	-0.073	0.930	-0.087	0.917	-0.067	0.935
Local bias ratio	-0.100	0.905	-0.091	0.913	-0.072	0.931	-0.062	0.940
Panel F : Date of participation								
Trading P-ETFs before MiFID (Dummy)	0.530***	1.699					0.115	1.122
Time before trading P-ETFs (in Months)			-0.017***	0.983			-0.012***	0.988
Year 2004					0.209	1.232	0.291	1.338
Year 2005					-0.169	0.845	0.033	1.034
Year 2006					-0.282	0.754	-0.022	0.978
Year 2007					-0.354*	0.702	0.048	1.049
Year 2008					-0.441**	0.643	0.164	1.178
Year 2009					-0.690***	0.502	-0.009	0.991
Year 2010					-0.852***	0.427	-0.039	0.962
Year 2011					-1.356***	0.258	-0.394	0.674
Year 2012					-1.805***	0.164	-0.730**	0.482
α (dispersion)	0.660***		0.607***		0.615***		0.595***	
N	2,015		2,015		2,015		2,015	
Log likelihood	16,829.87		16,907.90		16,899.84		16,929.24	
AIC	11,159.90		11,002.82		11,034.96		10,980.14	
BIC	11,282.28		11,126.21		11,203.21		11,159.61	

This table reports the results of four Negative Binomial regressions. The dependent variable is the number of P-ETF trades. In addition to the previous Panles (A, B, C and D) this Table includes Panel F refers to participation dates. 'Trading P-ETFs before MiFID' is a dummy variable equal to one if the investor had trade P-ETFs before introduction of MiFID (01/11/2007). 'Time before trading P-ETFs' is computed as the number of months between the date of the first trade and the date of the first P-ETF trade.'year2003'- 'year2012' are dummies for the year of the first P-ETFs trade, where 'year2003' is the reference category. 'IRR' is the incidence rate ratio, which is equal to the exponential of the coefficient estimate. *, **, *** indicate that the coefficient estimate is statistically significant at 10%, 5% or 1%, respectively.

6.2 Trading behavior of passive ETF retail investors

Table 6.4: Results of the logit model for the propensity score matching

ETF	Estimates	P-value
Intercept	-3.80	< 0.00
English speaking	0.71	< 0.00
Higher education	0.27	0.01
Financial knowledge	0.28	< 0.00
Financial experience	-0.02	0.07
Portfolio value	0.00	0.022
Pseudo R^2	0.018	
N	14,134	

This table reports the parameter estimates for a logit model wherein the dependent variable, Y_i , is a binary variable that equals 1 if investor i traded at least once P-ETFs during the sample period and 0 otherwise. 'English speaking' is a dummy=1 if the investor speaks English; 'Higher of education' is a dummy=1 if the investor holds a university degree or equivalent; and 'Financial knowledge', 'Financial experience' and 'portfolio value' are the monthly average end-of-month portfolio market values in €.

Table 6.5: ANOVA results – trading activity measures (aggregate portfolio).

Weight of P-ETF in aggregate portfolio	TG-1 < $Q_1 = 0.1291$ n=128	TG-2 > $Q_1 = 0.1291$ & < $Q_2 = 0.2746$ n=128	TG-3 > $Q_2 = 0.2746$ & < $Q_3 = 0.5883$ n=128	TG-4 > $Q_3 = 0.5883$ n=128	F-stat
Number of observations	Mean	Mean	Mean	Mean	
Panel A: Trades-based variables					
Number of trades	136.84	61.96	38.38	34.27	18.7***
Number of purchases	85.99	40.26	24.63	20.82	23.97***
Number of sales	54.69	23.74	15.71	14.98	11.41***
Trading volume	4,770.98	4,347.39	3,878.18	6,904.8	3.38**
Buying volume	4,844.06	4,135.07	3,684.38	6,653.60	3.07**
Selling volume	4,978.62	5,120.11	4,403.96	7,882.48	3.10**
Trading experience	53.80	48.83	44.63	45.04	3.88***
Trade duration	31.12	50.65	80.69	104.93	23.66***
Number of different securities traded	35.39	21.20	12.83	10.09	54.78***
Number of trading days	83.34	43.64	28.50	27.67	28.91***
Panel B: Portfolio-based variables					
Portfolio size	12.87	7.44	4.70	2.76	97.08***
Value of the portfolio	114,580.38	40,927.39	27,029.29	30,442.19	4.58***
Turnover	4.57	0.24	0.88	0.33	0.99
Portfolio holding period	62.32	58.13	57.71	58.95	0.94
Asset holding period ratio (HPR)	0.664	0.679	0.678	0.591	3.21**

The table reports the results for the analysis of variance (ANOVA) on the relationship between several variables characterizing trading behaviour and the weight of P-ETFs in the aggregate portfolio. For each variable under scrutiny, we report its mean for each TG-i group. Panel A includes trades-based variables. 'Number of trades' is the number of trades executed across the two assets (Stocks and P-ETFs). 'Number of purchases' is the number of purchases executed over the sample period. 'Number of sales' is the number of sales executed over the sample period. 'Trading volume' is the volume in (€) of trades executed over the sample period. 'Buying volume' is the volume in (€) of purchases executed over the sample period. 'Selling volume' is the volume in (€) of sales executed over the sample period. 'Trading experience' is computed as the difference between the last and the first trading dates, expressed in number of months. 'Trade duration' is computed as the average number of days between two consecutive trades. 'Number of different securities traded' is the number of different securities traded during the whole period. 'Number of trading days' is the total number of different trading days during the whole trading period. Panel B includes portfolio-based variables. 'Portfolio size' is the average number of securities held in the end-of-month portfolio. 'Value of the portfolio' is the average value of the end-of-month portfolio. 'Turnover' is the average of the absolute values of all of the purchases and sales in a particular month divided by the average of the portfolio values at the beginning and the end of this particular month. 'Portfolio holding period' is the number of months between the first month with a nonempty portfolio and the last month with a nonempty portfolio, over the sample period (January 2003-March 2012). 'Asset holding period ratio' is asset average holding period in the portfolio, expressed as a percentage of 'Portfolio holding period'.

*, **, *** indicate that the difference is statistically significant at the level of 10%, 5% or 1%, respectively.

Table 6.6: Comparaision between TG-i groups (aggregate portfolios) and PSM-RG (stock portfolio).

		TG-1 n=128	TG-2 n=128	TG-3 n=128	TG-4 n=128	PSM-RG n=511	t-test				
Metrics		Mean	Mean	Mean	Mean	Mean	Diff-1	Diff-2	Diff-3	Diff-4	Diff-5
		(1)	(2)	(3)	(4)	(5)	(1)-(4)	(1)-(5)	(2)-(5)	(3)-(5)	(4)-(5)
Panel A: Trades-based variables											
Number of trades		136.84	61.96	38.38	34.27	59.39	102.6***	77.45***	2.58	-21.01***	-25.11***
Number of purchases		85.99	40.26	24.63	20.82	35.21	65.18***	50.78***	5.04	-10.59***	-14.40***
Number of sales		54.69	23.74	15.71	14.98	26.85	39.71***	27.84***	-3.11	-11.14***	-11.87***
Trading volume	(in €)	4,770.98	4,347.39	3,878.18	6,904.8	6,055.3	-2,133*	-1,284.4	-1,708.0*	-2,177.2***	848.7
Buying volume	(in €)	4,844.06	4,135.07	3,684.38	6,653.60	5,753.9	-1,809.5	-909.8	-1,618.8*	-2,069.5***	899.7
Selling volume	(in €)	4,978.62	5,120.11	4,403.96	7,882.48	6,968.8	-2,903.9**	-1,990.1**	-1,848.6*	-2,564.8**	913.7
Trading experience	(in months)	53.80	48.83	44.63	45.04	42.52	8.77***	11.28***	6.30**	2.11	2.51
Trade duration	(in days)	31.12	50.65	80.69	104.93	98.08	-73.81***	-66.96***	-47.43***	-17.39	6.85
Number of different securities traded		35.39	21.20	12.83	10.09	13.38	25.30***	22.01***	7.82***	-0.55	-3.28***
Number of trading days		83.34	43.64	28.50	24.67	38.10	58.67***	45.25***	5.54	-9.60**	-13.42***
Panel B: Portfolio-based variables											
Portfolio size		12.87	7.44	4.70	2.76	4.00	10.11***	8.87***	3.44***	0.70*	-1.24***
Value of the portfolio	(in €)	114,580.38	40,927.39	27,029.29	30,442.19	38,276.5	84,138.2**	76,303.9*	2,650.9	-11,247.2	-7,834.3
Turnover		4.57	0.24	0.88	0.33	1.38	4.24	3.18	-1.14**	-0.50	-1.05*
Portfolio holding period	(in months)	62.32	58.13	57.71	58.95	57.63	3.36	4.68*	0.49	0.08	1.32
Asset holding period ratio (HPR)		0.66	0.68	0.68	0.59	0.61	0.07**	0.05**	0.07***	0.07***	-0.02

The table reports the cross-sectional mean and means differences between TG-i groups (aggregate portfolios) and PSM-RG (Stocks portfolio). For each variable under scrutiny, we report its mean for each group. Panel A includes trades-based variables. 'Number of trades' is the number of trades executed over the sample period. 'Number of purchases' is the number of purchases executed over the sample period. 'Number of sales' is the number of sales executed over the sample period. 'Trading volume' is the volume in (€) of trades executed over the sample period. 'Buying volume' is the volume in (€) of purchases executed over the sample period. 'Selling volume' is the volume in (€) of sales executed over the sample period. 'Trading experience' is computed as the difference between the last and the first trading dates, expressed in number of months. 'Trade duration' is computed as the average number of days between two consecutive trades. 'Number of different securities traded' is the number of different securities traded during the whole period. 'Number of trading days' is the total number of different trading days during the whole trading period. Panel B includes portfolio-based variables. 'Portfolio size' is the average number of securities held in the end-of-month portfolio. 'Value of the portfolio' is the average value of the end-of-month portfolio. 'Turnover' is the average of the absolute values of all of the purchases and sales in a particular month divided by the average of the portfolio values at the beginning and the end of this particular month. 'Portfolio holding period' is the number of months between the first month with a nonempty portfolio and the last month with a nonempty portfolio over the sample period (January 2003-March 2012). 'Asset holding period ratio' is asset average holding period in a portfolio, expressed as percentage of 'Portfolio holding period'.

*, **, *** indicate that the difference is statistically significant at the level of 10%, 5% or 1%, respectively.

Table 6.7: Univariate *t*-test comparisons between sub-TG and PSM-RG investors.

Weight of P-ETF in aggregate portfolio	TG1	TG2	TG3	TG4	PSM-RG	t-test				
	0 – 25% n=377	25% – 50% n=70	50% – 75% n=41	75% – 100% n=24	0% n=511					
	Mean (1)	Mean (2)	Mean (3)	Mean (4)	Mean (5)	Diff-1 (1)-(4)	Diff-2 (1)-(5)	Diff-3 (2)-(5)	Diff-4 (3)-(5)	Diff-5 (4)-(5)
Metrics										
Panel A: Aggregate portfolio										
Arithmetic net excess return (annualized)	-0.042	-0.089	-0.077	-0.040	-0.203	-0.002	0.161***	0.114**	0.127***	0.163***
Volatility (annualized)	0.293	0.291	0.241	0.226	0.422	0.067	-0.129***	-0.131***	-0.181***	0.196***
Panel B: Core portfolio										
Arithmetic net excess return (annualized)	0.001	-0.051	-0.051	-0.035	-0.203	0.036*	0.204***	0.152***	0.152***	0.168***
Volatility (annualized)	0.198	0.218	0.202	0.207	0.422	-0.009	-0.224***	-0.204***	-0.220***	-0.215***
Panel C: Satellite portfolio										
Arithmetic net excess return (annualized)	-0.045	-0.081	-0.081	0.057	-0.203	-0.102***	0.158***	0.122**	0.122***	0.260***
Volatility (annualized)	0.304	0.338	0.323	0.406	0.422	-0.102***	-0.118***	-0.084***	0.099***	-0.016

The table reports the cross-sectional mean and means differences between TG-i groups (aggregate, core and satellite portfolios) and PSM-RG (Stocks portfolio).

*, **, *** indicate that the difference is statistically significant at the level of 10%, 5% or 1%, respectively.

Table 6.8: P-ETF investors' trading behaviours.

		Portfolio size		Log(Turnover)		AHPR	
		(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Variable of interest							
TG	Dummy =1 if P-ETF user	2.950***		-0.418***		0.044***	
TG1	Dummy =1 if P-ETF user in TG1		6.052***		-0.287***		0.0588***
TG2	Dummy =1 if P-ETF user in TG2		1.230***		-0.582***		0.083***
TG3	Dummy =1 if P-ETF user in TG3		0.5151		-0.737***		0.054
TG4	Dummy =1 if P-ETF user in TG4		-1.557***		-0.314**		-0.054*
Panel B: Socio-demographic variables							
Age	Years	0.116***	0.091***	-0.006**	-0.007**	0.001	0.001
Gender	Dummy=1 if male	0.745	0.711*	0.083	0.077	-0.052**	-0.051**
Higher education	Dummy=1 if university	0.266	0.185	-0.188**	-0.183**	0.083***	0.080***
Dutch speaking	Dummy=1 if Dutch	1.328***	1.218***	-0.088	-0.082	0.025	0.020
English speaking	Dummy=1 if English	-0.029	0.383	-0.414***	-0.381***	0.021	0.021
Panel C: Subjective variables							
Knowledge of financial markets	(score 0-3)	0.276	0.251	-0.095*	-0.102*	-0.001	0.000
Knowledge of 'complex' instruments	(score 0-18)	0.068	0.094	0.004	0.003	0.001	0.001
Experience with 'complex' instruments	(score 0-18)	-0.052	-0.066	0.021	0.023	-0.000	-0.004
Awareness of the losses of 'complex' instruments	(score 0-9)	-0.09	-0.046	-0.011	-0.011	0.000	-0.001
Intercept		-3.433***	-1.933**	-0.944***	-0.903***	0.564**	0.578***
Adjusted R^2		0.156	0.310	0.050	0.058	0.020	0.032
N		1,023	1,023	1,023	1,023	1,023	1,023

Note: this table reports the results of cross-sectional regressions in which the dependent variables are the portfolio sizes for models (1) and (2), the logarithm of turnover for models (3) and (4) and the Asset Holding Period Ratio (AHPR) for models (5) and (6). Panel A includes variables of interest. 'TG' is a dummy variable set to 1 if investor holds a P-ETF and 0 otherwise. 'TG1', 'TG2', 'TG3' and 'TG4' are dummies characterizing the weight of P-ETFs in the aggregate portfolio with four intervals of 25% range spread (i.e., [0%-25%], [25%-50%], [50%-75%] and [75%-100%] respectively). Panel B refers to sociodemographics as control variables. 'Age' is determined as the difference between 2012 and the investor's year of 'birth'. 'Gender' is a dummy variable equal to one if the investor is a male. 'Higher Education' is a dummy variable set to one for investors with a university degree (or equivalent). 'Dutch speaking' and 'English speaking' are both dummies based on the language selected by the investor on the online trading platform. Panel C includes subjective variables (from the A-test). 'Knowledge of financial markets' refers to one specific question for which investors must self-assess their knowledge of financial markets on a scale of four levels, wherein Level 0 is associated with a basic knowledge, while Level 3 refers to an experienced investor 'who manages any aspect of the financial markets'. For 'Knowledge of "complex" instruments', 'Experience with "complex" instruments' and 'Awareness of the losses with "complex" instruments', the score elicits the investor's self-assessment regarding his/her own abilities and skills. For example, a score of 18 out of 18 for 'Knowledge of "complex" instruments' indicates that the investor considers himself/herself as an expert in the field. Conversely, a score of 0 (out of 18) indicates that the investor declares no knowledge about "complex" instruments. 'Appetite for information' is binary variable with a value of 1 if the investor has asked for access to the information tool on stocks and has completed the S-test and 0 otherwise. *, **, *** indicate that the coefficient is statistically significant at the level of 10%, 5% or 1%, respectively.

Table 6.9: Univariate ANOVA comparisons between sub-TG investors for core and satellite portfolios.

		TG1	TG2	TG3	TG4	F-stat
Weight of P-ETF in aggregate portfolio		0 – 25% n=377	25% – 50% n=70	50% – 75% n=41	75% – 100% n=24	
Metrics		Mean (1)	Mean (2)	Mean (3)	Mean (4)	
Panel A: Core portfolio						
Number of trades		3.82	5.17	9.46	17.54	13.11***
Number of purchases		2.59	3.84	6.68	13.96	15.98***
Number of sales		2.05	2.81	3.93	6.61	6.23***
Trading volume	(in €)	5,136.82	5,300.58	9,976.55	7,101.15	3.27**
Buying volume	(in €)	4,980.92	5,163.66	10,600.67	6,406.27	4.05***
Selling volume	(in €)	6,064.74	7,497.65	12,417.37	13,904.11	3.17**
Panel B: Satellite portfolio						
Number of trades		78.98	20.66	16.22	10.25	7.89***
Number of purchases		49.30	13.57	10.17	6.95	9.65***
Number of sales		32.06	9.73	7.09	3.95	4.33***
Trading volume	(in €)	4,712.99	3,830.37	8,109.59	2,716.76	2.96**
Buying volume	(in €)	4,600.13	3,694.94	8,211.63	2,486.22	2.99**
Selling volume	(in €)	5,168.32	4,376.37	7,587.78	3862.52	1.04

The table reports the results for the analysis of variance (ANOVA) on the relationship between several variables characterizing trading behaviour and the weight of P-ETFs in the aggregate portfolio. For each variable under scrutiny, we report its mean for each TG-i group. Panel A includes trades-based variables. 'Number of trades' is the number of trades executed across the two assets (Stocks and P-ETFs). 'Number of purchases' is the number of purchases executed over the sample period. 'Number of sales' is the number of sales executed over the sample period. 'Trading volume' is the volume in (€) of trades executed over the sample period. 'Buying volume' is the volume in (€) of purchases executed over the sample period. 'Selling volume' is the volume in (€) of sales executed over the sample period. (aggregate, core and satellite portfolios) and PSM-RG (Stocks portfolio). *, **, *** indicate that the difference is statistically significant at the level of 10%, 5% or 1%, respectively.

Table 6.10: Results of panel regressions

		$LP_{i,t}^1$		$LP_{i,t}^2$	
		(1)	(2)	(3)	(4)
Panel A: Variables of interest					
Hold P-ETF	Dummy =1 if investor hold P-ETF	-0.280***		-0.211**	
TG1	Dummy if P-ETF user in TG1		-2.751***		-0.325***
TG2	Dummy if P-ETF user in TG2		-1.197***		0.029
TG3	Dummy if P-ETF user in TG3		-3.677***		-0.475**
TG4	Dummy if P-ETF user in TG4		-5.817***		-1.060**
Financial crisis 2008	Dummy	2.480***	2.475***	1.779***	1.796***
Panel B: Socio-demographic variables					
Age	In years	-0.026***	-0.029***	0.010***	0.010***
Gender	Dummy	0.337**	0.348**	0.113	0.115
Higher education	Dummy	-0.741***	-0.775***	-0.357***	-0.352***
Dutch speaking	Dummy	0.054	0.040	0.298***	0.298***
English speaking	Dummy	-0.619***	-0.583***	-0.182*	-0.166*
Panel C: Subjective variables					
Knowledge of financial markets	Score 0-3	0.088	0.184***	0.022	0.032
Knowledge of 'complex' instruments	Score 0-18	-0.091***	-0.069***	-0.006	-0.002
Experience with 'complex' instruments	Score 0-18	0.095***	0.064***	0.018	0.014
Awareness of the losses of 'complex' instruments	Score 0-9	0.033**	0.028*	-0.018*	-0.019*
Appetite for information	Dummy	-0.676***	-0.447***	-0.022	0.004

Note: this table reports the results of the panel regressions, where the dependent variables are $LP_{i,t}^1$ for models (1) and (2) and $LP_{i,t}^2$ for models (3) and (4). Panel A includes variables of interest. 'TG' is a dummy variable set to 1 if an investor holds a P-ETF and 0 otherwise. 'TG1', 'TG2', 'TG3' and 'TG4' are dummies characterizing the weight of P-ETFs in the aggregate portfolio with four intervals of 25% range spread (i.e., [0%-25%], [25%-50%], [50%-75%] and [75%-100%] respectively). 'Financial crisis 2008' is dummy variable set to 1 if the month is between September 2008 and June 2009 and 0 otherwise. Panel B refers to sociodemographics as control variables. 'Age' is determined as the difference between 2012 and the investor's year of 'birth'. 'Gender' is a dummy variable equal to one if the investor is a male. 'Higher Education' is a dummy variable set to one for investors with a university degree (or equivalent). 'Dutch speaking' and 'English speaking' are both dummies based on the language selected by the investor on the online trading platform. Panel C includes subjective variables (from the A-test). 'Knowledge of financial markets' refers to one specific question for which investors must self-assess their knowledge of financial markets on a scale of four levels, wherein Level 0 is associated with a basic knowledge, while Level 3 refers to an experienced investor 'who manages any aspect of the financial markets'. For 'Knowledge of "complex" instruments', 'Experience with "complex" instruments' and 'Awareness of the losses with "complex" instruments', the score elicits the investor's self-assessment regarding his/her own abilities and skills. For example, a score of 18 out of 18 for the 'Knowledge of "complex" instruments' means that the investor considers himself/herself an expert in the field. Conversely, a score of 0 (out of 18) indicates that the investor declares no knowledge about "complex" instruments. 'Appetite for information' is binary variable with a value of 1 if the investor has asked for an access to the information tool on stocks and has completed the S-test and 0 otherwise. *, **, *** indicate that the coefficient is statistically significant at the level of 10%, 5% or 1%, respectively.

Table 6.11: Results of panel regressions

		$LP_{i,t}^1$		$LP_{i,t}^2$	
		(1)	(2)	(3)	(4)
Panel A: Variables of interest					
Hold P-ETF	Dummy =1 if investor hold P-ETF	-0.640***		0.066	
TG1	Dummy if P-ETF user in TG-1		-2.006***		-0.547***
TG2	Dummy if P-ETF user in TG-2		-1.257***		-0.003
TG3	Dummy if P-ETF user in TG-3		-2.918***		-0.301
TG4	Dummy if P-ETF user in TG-4		-4.331***		-0.785***
Financial crisis 2008	Dummy	1.725***	1.716***	1.476***	1.146***
Panel B: Socio-demographic variables					
Age	In years	-0.031***	-0.037***	-0.006***	-0.008***
Gender	Dummy	0.171	0.144	-0.097	-0.109
Higher education	Dummy	-0.416***	-0.424***	-0.267***	-0.272***
Dutch speaking	Dummy	0.411***	0.356***	0.112*	0.098
English speaking	Dummy	0.677***	0.699***	-0.251***	-0.252***
Panel C: Subjective variables					
Knowledge of financial markets	Score 0-3	-0.084	-0.036	-0.067	-0.054
Knowledge of 'complex' instruments	Score 0-18	-0.063***	-0.049***	-0.008	-0.005
Experience with 'complex' instruments	Score 0-18	0.089***	0.068***	0.016	0.011
Awareness of the losses of 'complex' instruments	Score 0-9	0.062***	0.059***	-0.005	-0.005
Appetite for information	Dummy	-0.900***	-0.791***	-0.199***	-0.164***
Panel D: Objective variables					
Number of trades		0.299***	0.281***	0.635***	0.630***
Trading experience	(in months)	0.043***	0.044***	0.011***	0.011***
Trade duration	(in days)	-0.002***	-0.002***	-0.002***	-0.002***
Number of different securities traded		0.001	0.011***	0.008***	0.011***

Note: this table reports the results of the panel regressions, where the dependent variables are $LP_{i,t}^1$ for models (1) and (2) and $LP_{i,t}^2$ for models (3) and (4). Panel A includes variables of interest. 'TG' is a dummy variable set to 1 if an investor holds a P-ETF and 0 otherwise. 'TG1', 'TG2', 'TG3' and 'TG4' are dummies characterizing the weight of P-ETFs in the aggregate portfolio with four intervals of 25% range spread (i.e., [0%-25%], [25%-50%], [50%-75%] and [75%-100%] respectively). 'Financial crisis 2008' is dummy variable set to 1 if the month is between September 2008 and June 2009 and 0 otherwise. Panel B refers to sociodemographics as control variables. 'Age' is determined as the difference between 2012 and the investor's year of 'birth'. 'Gender' is a dummy variable equal to one if the investor is a male. 'Higher Education' is a dummy variable set to one for investors with a university degree (or equivalent). 'Dutch speaking' and 'English speaking' are both dummies based on the language selected by the investor on the online trading platform. Panel C includes subjective variables (from the A-test). 'Knowledge of financial markets' refers to one specific question for which investors must self-assess their knowledge of financial markets on a scale of four levels, wherein Level 0 is associated with a basic knowledge, while Level 3 refers to an experienced investor 'who manages any aspect of the financial markets'. For 'Knowledge of "complex" instruments', 'Experience with "complex" instruments' and 'Awareness of the losses of "complex" instruments', the score elicits the investor's self-assessment regarding his/her own abilities and skills. For example, a score of 18 out of 18 for the 'Knowledge of "complex" instruments' means that the investor considers himself/herself an expert in the field. Conversely, a score of 0 (out of 18) indicates that the investor declares no knowledge about "complex" instruments. 'Appetite for information' is binary variable with a value of 1 if the investor has asked for an access to the information tool on stocks and has completed the S-test and 0 otherwise. Panel D includes objective variables characterizing trading activity. 'Number of trades' is the number of trades executed over the sample period. 'Trading experience' is computed as the difference between the last and the first trading dates, expressed in the number of 'months'. 'Trade duration' is computed as the average number of days between two consecutive trades. 'Number of different stocks traded' is the number of different stocks traded. *, **, *** indicate that the coefficient is statistically significant at the level of 10%, 5% or 1%, respectively.

Table 6.12: Results of panel regressions

		$LP_{i,t}^1$		$LP_{i,t}^2$	
		(1)	(2)	(3)	(4)
Panel A: Variables of interest					
Hold P-ETF	Dummy =1 if investor hold P-ETF	-0.562**		0.136	
TG1	Dummy if P-ETF user in TG-1		-2.036***		-0.561***
TG2	Dummy if P-ETF user in TG-2		-1.134***		0.103
TG3	Dummy if P-ETF user in TG-3		-2.775***		-0.220
TG4	Dummy if P-ETF user in TG-4		-4.286***		-0.688***
% of trades during financial crisis 2008		-1.385***	-1.252***	0.088	0.874
Panel B: Socio-demographic variables					
Age	In years	-0.032***	-0.037***	-0.006***	-0.008***
Gender	Dummy	0.181*	0.154	-0.097	-0.111
Higher education	Dummy	-0.418***	-0.426***	-0.269***	-0.275***
Dutch speaking	Dummy	0.419***	0.365***	0.111*	0.096
English speaking	Dummy	0.622***	0.682***	-0.254**	-0.256**
Panel C: Subjective variables					
Knowledge of financial markets	Score 0-3	-0.091*	-0.043	-0.066*	-0.053
Knowledge of 'complex' instruments	Score 0-18	-0.065***	-0.051***	-0.008	-0.005
Experience with 'complex' instruments	Score 0-18	0.092***	0.071***	0.016	0.011
Awareness of the losses of 'complex' instruments	Score 0-9	0.065***	0.063***	-0.005	-0.005
Appetite for information	Dummy	-0.889***	-0.776***	-0.199***	-0.162***
Panel D: Objective variables					
Number of trades		0.309***	0.292***	0.643***	0.638***
Trading experience	(in months)	0.042***	0.042***	0.011***	0.011***
Trade duration	(in days)	-0.002	-0.002***	-0.002***	-0.002***
Number of different securities traded		-0.001	0.010***	0.008**	0.011***

Note: this table reports the results of the panel regressions, where the dependent variables are $LP_{i,t}^1$ for models (1) and (2) and $LP_{i,t}^2$ for models (3) and (4). Panel A includes variables of interest. 'TG' is a dummy variable set to 1 if an investor holds a P-ETF and 0 otherwise. 'TG1', 'TG2', 'TG3' and 'TG4' are dummies characterizing the weight of P-ETFs in the aggregate portfolio with four intervals of 25% range spread (i.e., [0%-25%], [25%-50%], [50%-75%] and [75%-100%] respectively). "% of trades during financial crisis 2008" is determined as the percentage of trades executed during the financial crisis 2008 (April 2008-March 2009) for investor i . Panel B refers to sociodemographics as control variables. 'Age' is determined as the difference between 2012 and the investor's year of 'birth'. 'Gender' is a dummy variable equal to one if the investor is a male. 'Higher Education' is a dummy variable set to one for investors with a university degree (or equivalent). 'Dutch speaking' and 'English speaking' are both dummies based on the language selected by the investor on the online trading platform. Panel C includes subjective variables (from the A-test). 'Knowledge of financial markets' refers to one specific question for which investors must self-assess their knowledge of financial markets on a scale of four levels, wherein Level 0 is associated with a basic knowledge, while Level 3 refers to an experienced investor 'who manages any aspect of the financial markets'. For 'Knowledge of "complex" instruments', 'Experience with "complex" instruments' and 'Awareness of the losses with "complex" instruments', the score elicits the investor's self-assessment regarding his/her own abilities and skills. For example, a score of 18 out of 18 for the 'Knowledge of "complex" instruments' means that the investor considers himself/herself an expert in the field. Conversely, a score of 0 (out of 18) indicates that the investor declares no knowledge about "complex" instruments. 'Appetite for information' is binary variable with a value of 1 if the investor has asked for an access to the information tool on stocks and has completed the S-test and 0 otherwise. Panel D includes objective variables characterizing trading activity. 'Number of trades' is the number of trades executed over the sample period. 'Trading experience' is computed as the difference between the last and the first trading dates, expressed in the number of 'months'. 'Trade duration' is computed as the average number of days between two consecutive trades. 'Number of different stocks traded' is the number of different stocks traded. *, **, *** indicate that the coefficient is statistically significant at the level of 10%, 5% or 1%, respectively.

6.3 Do stock retail investors show better portfolio performance when they hold passive ETFs?

6.3.1 Details on the Propensity Score Matching

The propensity score is computed for each investor in the sample, and is equal to the estimated probability that a retail investor would trade P-ETFs at least once during the sample period conditioned on a set of regressors, X . This probability is given by $Prob[Y = 1|X] = G(x'b)$, where $G(\cdot)$ is the logistic cumulative distribution function. Thus, in our logit model (1) below, we opt for a random matching procedure that controls for sociodemographics, portfolio value and subjective variables from the A-test.

$$P(Y_i = 1|SDV_i; SV_i; OV_i) = G(\beta_0 + \beta_1 SDV_i + \beta_2 SV_i + \beta_3 OV_i + \epsilon_i) \quad (6.1)$$

where $Y_i = PETF_i$, which is a dummy variable set to 1 if each investor i trades stock P-ETFs at least once. SDV_i is a vector of socio-demographic attributes including age, gender, level of education and spoken language of each investor i . OV_i is an objective variable measuring the portfolio value in euros of each investor i . SV_i is the vector of subjective variables based on survey-data, including financial knowledge and experience of each investor i .

To obtain a relevant estimation of the matching scores, we only retain the significant variables in the previous logistic model by following the general to specific approach with a 10% threshold. The final logistic model (2) used to estimate the matching score,

includes the following five explanatory variables:

$$P(Y_i = 1|X) = G(\beta_0 + \beta_1 \text{Age}_i + \beta_2 \text{Eng-spe}_i + \beta_3 \text{Hig-edu}_i + \beta_4 \text{Kno-fin-mark}_i + \beta_5 \text{App-inf}_i + \beta_5 \text{Num-diff-sec}_i + \beta_6 \text{Num-tra-day}_i + \beta_7 \text{Tra-exp}_i + \epsilon_i) \quad (6.2)$$

where $Y_i = PETF_i$, Age_i is investor age in years in 2012; Eng-spe_i is a dummy equal to 1 if investor i speaks English and 0 otherwise; Hig-edu_i is a dummy equal to 1 if investor i holds a university degree or equivalent and 0 otherwise; Kno-fin-mark_i refers to one specific question in which investors must self-assess their knowledge of financial markets on a scale of four levels, wherein Level 0 is associated with basic knowledge, while Level 3 refers to an experienced investor 'who manages any aspect of the financial markets'; App-inf is dummy variable with a value of 1 if the investor has asked for an access to the information tool on stocks and has completed the S-test and 0 otherwise; Num-diff-sec is the number of different securities traded during the whole period ; Num-tra-day is the total number of different trading days during the whole trading period ; and Tra-exp_i is computed as the difference between the last and the first trading dates, expressed in number of months.

There are numerous ways to match individuals assigned to different groups based on propensity scores.¹ We opt for a matching based on an allowable absolute difference between exact propensity scores, i.e., based on a radius around the score matching.² This method allows us to end up with a sample of 444 investors in the RG.

The results of the logit model (2) for propensity score matching are given below in Table

¹Among them, the nearest neighbor matching, radius matching, kernel matching, and interval matching.

²Each treated observation i is matched with control observations j as long as their absolute difference in propensity scores (PS) falls within a specified radius, r , such that $||PS_i - \hat{PS}_j|| < r$. The lower r , the higher the level of closeness we require. In our case, r is set to 0.01. We choose the lowest radius possible to get a very similar number of observations to the TG, keeping the differences between the TG and the RG (after PSM) no longer significant.

Table 6.13: Results of the logit model for the propensity score matching

ETF	Estimates	P-value
Intercept	-4.238	< .000
Age	-0.006	0.095
English speaking	0.727	< .000
Higher education	0.392	0.001
Knowledge financial markets	0.143	0.010
Appetite for information	0.263	0.008
Number of different securities traded	0.045	< .000
Number of different trading days	-0.011	< .000
Trading experience	0.013	< .000
N	13,129	

This table reports the parameter estimates for a logit model wherein the dependent variable, Y_i , is a binary variable that equals 1 if investor i traded at least once P-ETFs during the sample period and 0 otherwise. 'English speaking' is a dummy=1 if the investor speaks English; 'Higher of education' is a dummy=1 if the investor holds a university degree or equivalent; and 'Financial knowledge'.

6.3.2 Trading activeness

Table 6.14: Comparisons between TG investors' P-ETF portfolios and RG investors' portfolios.

Weight of P-ETF in aggregate portfolio	LTG]0% – 50%[n=416	HTG [50% – 100%] n=47	RG 0% n=444	Wilcoxon rank-sum test		
	Median (1)	Median (2)	Median (3)	p-value (1)-(2)	p-value (1)-(3)	p-value (2)-(3)
Panel A: Trades-based variables						
Number of trades	2.000	3.000	20.000	0.279	< .000	< .000
Trading experience	5.000	16.000	33.000	0.008	< .000	< .000
Trade duration	111.429	96.720	37.865	0.235	< .000	< .000
Number of different securities traded	1.000	1.000	8.000	0.020	< .000	< .000
Number of trading days	2.000	3.000	16.000	0.254	< .000	< .000
Panel B: Portfolio-based variables						
Portfolio size	1.000	1.000	4.265	0.006	< .000	< .000
Portfolio value (in eur)	629.968	6,635.550	10,779.061	< .000	< .000	< .000

The table reports the cross-sectional median and median differences between TG investors' P-ETF portfolios and RG investors' portfolio, on a per investor basis over the sample period. 'Number of trades' is the number of trades executed across all securities. 'Turnover' is the monthly average turnover. It is calculated as in Hoffmann et al. (2013), i.e. average of the absolute values of all purchases and sales in a particular month divided by the average of the portfolio values at the beginning and the end of this particular month. 'Trading experience' is computed as the difference between the last trade date and the first trade date available in the sample. It is expressed in number of months. 'Trade duration'. 'Number of different securities traded' is the number of different securities traded during the whole trading period. 'Number of trading days'. 'Portfolio size' is the monthly average number of stocks held in portfolio. 'Portfolio value' is the monthly average portfolio market value. *, **, *** indicate that the difference is statistically significant at the level of 10%, 5% or 1%, respectively.

Table 6.15: Comparisons between TG investors' stock portfolios and RG investors' portfolios.

Weight of P-ETF in aggregate portfolio	LTG	HTG	RG	Wilcoxon rank-sum test		
	]0% – 50%[n=416	[50% – 100%] n=47	0% n=444			
Metrics	Median (1)	Median (2)	Median (3)	p-value (1)-(2)	p-value (1)-(3)	p-value (2)-(3)
Panel A: Trades-based variables						
Number of trades	20.000	5.000	20.000	< .000	0.966	< .000
Trading experience	35.000	16.000	33.000	< .000	0.388	< .000
Trade duration	43.296	85.231	37.865	< .000	0.275	< .000
Number of different securities traded	9.000	2.000	8.000	< .000	0.298	< .000
Number of trading days	15.500	4.000	16.000	< .000	0.991	< .000
Panel B: Portfolio-based variables						
Portfolio size	4.924	1.819	4.265	< .000	0.010	< .000
Portfolio value (in eur)	12,622.442	6,991.189	10.779.061	< .000	0.031	0.011

The table reports the cross-sectional median and median differences between TG investors' aggregate portfolios and RG , on a per investor basis over the sample period. 'Number of trades' is the number of trades executed across all securities. 'Turnover' is the monthly average turnover. It is calculated as in Hoffmann et al. (2013), i.e. average of the absolute values of all purchases and sales in a particular month divided by the average of the portfolio values at the beginning and the end of this particular month. 'Trading experience' is computed as the difference between the last trade date and the first trade date available in the sample. It is expressed in number of months. 'Trade duration'. 'Number of different securities traded' is the number of different securities traded during the whole trading period. 'Number of trading days'. 'Portfolio size' is the monthly average number of stocks held in portfolio. 'Portfolio value' is the monthly average portfolio market value. *, **, *** indicate that the difference is statistically significant at the level of 10%, 5% or 1%, respectively.

Table 6.16: Comparisons between TG investors' aggregate portfolios and RG investors' portfolios.

Weight of P-ETF in aggregate portfolio	LTG	HTG	RG	t-test		
	0% – 50% n=416	[50% – 100%] n=47	0% n=444			
	Mean (1)	Mean (2)	Mean (3)	Diff-1 (1)-(2)	Diff-2 (1)-(3)	Diff-3 (2)-(3)
Panel A: Trades-based variables						
Number of trades	50.426	13.532	44.079	36.894***	6.347	-30.547***
Turnover	0.767	0.042	0.775	0.425	-0.008	-0.733*
Trading experience	31.332	19.667	30.014	11.665***	1.318	-10.347***
Trade duration	82.893	141.100	82.269	-58.256***	0.624	58.880**
Number of different securities traded	15.471	5.021	13.750	10.449***	1.721*	-8.729***
Number of trading days	30.014	6.575	28.842	23.440***	1.172	-22.268***
Panel B: Portfolio-based variables						
Portfolio size	6.951	2.405	5.827	4.547***	1.124***	-3.422***
Portfolio value (in eur)	33,041.8	27,024.5	34,364.4	6,017.3	-1,322.7	-7,340.0

The table reports the cross-sectional mean and means differences between TG investors' aggregate portfolios and RG investors' portfolio, on a per investor basis over the sample period. 'Number of trades' is the number of trades executed across all securities. 'Turnover' is the monthly average turnover. It is calculated as in Hoffmann et al. (2013), i.e. average of the absolute values of all purchases and sales in a particular month divided by the average of the portfolio values at the beginning and the end of this particular month. 'Trading experience' is computed as the difference between the last trade date and the first trade date available in the sample. It is expressed in number of months. 'Trade duration'. 'Number of different securities traded' is the number of different securities traded during the whole trading period. 'Number of trading days'. 'Portfolio size' is the monthly average number of stocks held in portfolio. 'Portfolio value' is the monthly average portfolio market value. *, **, *** indicate that the difference is statistically significant at the level of 10%, 5% or 1%, respectively.

6.3.3 Correlation matrix among objective variables.

Table 6.17: Correlation coefficients - objective variables.

	Number of trades	Trading experience	Trade duration	Number of different securities traded	Number of trading days	Turnover	Portfolio size
Number of trades	1.000						
Trading experience	0.222	1.000					
Trade duration	-0.225	0.036	1.000				
Number of different securities traded	0.674	0.409	-0.343	1.000			
Number of trading days	0.883	0.367	-0.309	0.764	1.000		
Turnover	0.131	0.018	-0.046	0.052	0.149	1.000	
Portfolio size	0.372	0.354	-0.236	0.633	0.413	0.039	1.000
Portfolio value	0.171	0.085	-0.073	0.138	0.164	-0.010	0.242

The table reports correlation matrix for the objective variables. 'Number of trades' is the number of trades executed across all securities. 'Turnover' is the monthly average turnover. It is calculated as in Hoffmann et al. (2013), i.e. average of the absolute values of all purchases and sales in a particular month divided by the average of the portfolio values at the beginning and the end of this particular month. 'Trading experience' is computed as the difference between the last trade date and the first trade date available in the sample. It is expressed in number of months. 'Trade duration'. 'Number of different securities traded' is the number of different securities traded during the whole trading period. 'Number of trading days'. 'Portfolio size' is the monthly average number of stocks held in portfolio. 'Portfolio value' is the monthly average portfolio market value.

6.3.4 Additional models for robustness checks.

Table 6.18: Explaining excess returns in TG investors' aggregate portfolio.

Dependent variable	Gross excess return			Net excess return		
	Estimate x 100 (1)	Estimate x 100 (2)	Estimate x 100 (3)	Estimate x 100 (4)	Estimate x 100 (5)	Estimate x 100 (6)
Explanatory variables						
Panel A : Variables of interest						
Intercept	-1.923	-1.514***	-1.510***	-2.157***	-1.712**	-1.707***
LTG (P-ETFs weight [0%-50%])	0.884	0.826	0.863	0.878	0.855	0.855
HTG (P-ETFs weight [50%-100%])	0.952	0.788	0.791	1.009	0.830	0.834
% of trades during financial crisis 2008 (Fin-crisis)	0.953*	0.819	0.813	0.999*	0.854	0.847
LTG*Fin-crisis	-0.986	-0.982	-0.997	-1.009*	-1.004	-1.022*
HTG*Fin-crisis	-1.079*	-0.945	-0.930	-1.112*	-0.976	-0.958
Panel B : Market factors						
Risk premium	96.256***	96.393***	96.414***	96768***	96.915***	96.940***
SMB	29.348***	29.457***	29.475**	29.259***	29.376***	29.396***
HML	29.374***	29.321***	29.317***	29.099***	29.041**	29.036***
MOM	-19.796***	-19.778***	-19.774***	-19.233***	-19.215***	-19.210***
Panel C: Socio-demographic variables						
Age	0.008*	0.005	0.005	0.0010	0.006	0.007
Gender	-0.092	-0.119	-0.087	-0.103	-0.135	-0.098
Higher education	0.214	0.170	0.188	0.267*	0.219	0.240
Dutch-speaking	0.102	0.120	0.115	0.109	0.129	0.124
English-speaking	0.463	0.509*	0.478	0.494*	0.546*	0.510*
Panel D : Subjective variables						
Knowledge of financial markets	-0.090	-0.078	-0.080	-0.073	-0.006	-0.062
Knowledge of 'complex' instruments	-0.001	-0.001	0.001	-0.001	-0.001	0.001
Experience with 'complex' instruments	0.020	0.021	0.018	0.020	0.022	0.019
Awareness of the losses of 'complex' instruments	-0.011	-0.017	-0.017	-0.017	-0.024	-0.023
Appetite for information	-0.212**		-0.195**	-0.245**		-0.224**
Overconfidence		-2.210***	-2.202***		-2.402***	-2.393***
Panel E : Objective variables						
Number of trades	-0.001	0.001	0.001	-0.002**	0.001	0.001
Trading Experience	0.010**	0.007	0.009	0.001*	0.006	0.07
Trade duration	-0.001	-0.001	-0.001	0.001	-0.001	-0.001
Turnover	-0.013***	-0.001	-0.001	-0.014***	-0.001	-0.001
Portfolio size	0.036**	0.021	0.022	0.042**	0.026	0.027
Portfolio value (in eur)	0.000	0.000	0.000	0.000	0.000	0.000
N	29,663	29,663	29,663	29,663	29,663	29,663
R ²	0.3786	0.3801	0.3802	0.3775	0.3793	0.3794

This table reports the results of panel regressions where the dependent variable is the gross excess return in models (1), (2) and (3) and net excess return in models (4), (5) and (6). Panel A includes the two explanatory variables of interest, LTG and HTG which are dummy variables equal 1 if investor i is in the target group of light and heavy P-ETF users respectively, 0 otherwise. “% of trades during financial crisis 2008” is determined as the percentage of trades executed during the financial crisis 2008 (April 2008-March 2009) for investor i . Panel B includes four market factors: ‘Risk premium’, ‘SMB’, ‘HML’ and ‘MOM’, which are the market, the size, the book-to-market and the momentum factors, respectively, for the European market which are provided by Eurofidai. Panel C includes Socio-demographics: ‘Age’ is determined as the difference between 2012 and the year of birth. ‘Gender’ is a dummy variable equal to one if the investor is a male. ‘Higher education’ refers to the proportion of investors who declare that they hold a university degree or equivalent. ‘Dutch-speaking’, ‘French-speaking’ and ‘English-speaking’ refer to the proportion of investors who choose Dutch, French, and English respectively as the main language on the online brokerage trading platform. Panel D includes subjective variables and refers to the A-test. ‘Knowledge of financial markets’ refers to one specific question where investors have to self-assess their knowledge of financial markets on a scale of four levels, wherein Level 0 is associated with a basic knowledge while Level 3 refers to an experienced investor ‘who manages any aspect of the financial markets’. For ‘Knowledge of “complex” instruments’, ‘Experience with “complex” instruments’ and ‘Awareness of the losses with “complex” instruments’, the score indicates the investor’s self-assessment regarding his/her own abilities and skills. For example, a score of 18 out of 18 for the Knowledge of “complex” instruments means that the investor considers himself/herself as an expert in the field. Conversely, a score of 0 (out of 18) indicates that the investor declares no knowledge about “complex” instruments. ‘Appetite for information’ is dummy variable with a value of 1 if the investor has asked for an access to the information tool on stocks and has completed the S-test and 0 otherwise. Panel E includes objective variables: ‘Number of trades’ is the number of trades executed across all securities. ‘Turnover’ is the monthly average turnover. It is calculated as in Hoffmann et al. (2013), i.e. average of the absolute values of all purchases and sales in a particular month divided by the average of the portfolio values at the beginning and the end of this particular month. ‘Trading experience’ is computed as the difference between the last trade date and the first trade date available in the sample. It is expressed in number of months. ‘Trade duration’. ‘Number of different securities traded’ is the number of different securities traded during the whole trading period. ‘Number of trading days’. ‘Portfolio size’ is the monthly average number of stocks held in portfolio. ‘Portfolio value’ is the monthly average portfolio market value. *, **, *** indicate that the difference is statistically significant at the level of 10%, 5% or 1%, respectively.

6.3.5 Adjusting for risk using individual time series and cross-sectional medians.

Table 6.19 reports the cross-sectional median of the portfolio measures and comparison of samples distribution between TG investors' PETF portfolio and RG portfolio, on a per investor basis over the sample period. We use Wilcoxon rank-sum test to compare samples distribution, and p-value of tests are reported in the last three columns.

Table 6.19: Comparison between TG investors' P-ETF portfolios and RG portfolios.

Weight of P-ETF in aggregate portfolio	LTG]0% – 50%[n=416	HTG [50% – 100%] n=47	RG 0% n=444	Wilcoxon rank-sum test		
	Median (1)	Median (2)	Median (3)	P-value (1)-(2)	P-value (1)-(3)	P-value (2)-(3)
Panel A : Return						
Arithmetic excess net return (annualized)	-0.007	-0.055	-0.115	0.007	< .000	< .000
Arithmetic excess gross return (annualized)	0.004	-0.054	-0.105	0.001	< .000	< .000
Panel B : Volatility						
Volatility (annualized)	0.188	0.205	0.405	0.099	< .000	< .000
Downside Deviation (annualized)	0.120	0.151	0.324	0.004	< .000	< .000
Panel C : One-factor model coefficients						
One-factor Alpha	-0.004	-0.004	-0.010	0.971	< .000	< .000
One-factor Beta	0.869	0.923	1.160	0.096	< .000	< .000
Panel D : Four-factor model coefficients						
Four-factor Alpha	-0.003	-0.004	-0.006	0.220	< .000	0.056
Four-factor Beta (Market premium)	0.808	0.930	0.977	0.092	< .000	0.114
Four-factor Beta (Size)	-0.081	-0.111	0.309	0.681	< .000	< .000
Four-factor Beta (HML)	0.001	0.127	0.211	0.346	< .000	0.035
Four-factor Beta (MOM)	-0.017	0.003	-0.172	0.071	0.008	0.002
Panel E : Risk-adjusted performance measures						
Sharpe Ratio	-0.038	-0.265	-0.342	0.009	< .000	0.006
Treynor Ratio (one-factor beta)	-0.007	-0.058	-0.099	0.008	< .000	< .000
Treynor Ratio (four-factor beta)	-0.018	-0.059	-0.104	0.080	< .000	< .000
Sortino ratio	-0.089	-0.371	-0.406	0.050	< .000	0.055

The table reports the cross-sectional median for IG-i groups (P-ETFs portfolio) and RG, on a per investor basis over the sample period.

When we focus for TG investors exclusively on their P-ETFs portfolio and we compare it to RG portfolio, we find that P-ETFs portfolio of P-ETFs investors (for both groups light and heavy P-ETFs investors) show statistically higher return, lower total and idiosyn-

cratic risk and higher risk-adjusted return relative to RG individual stocks portfolio. Nevertheless, all these favorable outcomes regarding P-ETFs part of the portfolio, TG investors still fail to achieve a positive risk-adjusted performance measures.

In Table 6.20, we focus on TG investors' individual stock portfolios and we compare it to RG investors' portfolio. We find TG investors (for both sub groups light and heavy) show statistically significantly higher return, lower total and idiosyncratic risk and higher risk-adjusted return relative to RG stock portfolio. However, all risk-adjusted performance measures are negative similarly to previous results, as regarding the aggregate and P-ETFs portfolios for TG investors.

Table 6.20: Comparison between TG investors' stock portfolios and RG investors' portfolios.

Weight of P-ETF in aggregate portfolio	LTG]0% – 50%[n=416	HTG [50% – 100%] n=47	RG 0% n=444	Wilcoxon rank-sum test		
	Median (1)	Median (2)	Median (3)	P-value (1)-(2)	P-value (1)-(3)	P-value (2)-(3)
Panel A : Return						
Arithmetic excess net return (annualized)	-0.050	-0.007	-0.115	0.185	< .000	< .000
Arithmetic excess gross return (annualized)	-0.038	-0.003	-0.105	0.365	< .000	< .000
Panel B : Volatility						
Volatility (annualized)	0.271	0.331	0.405	0.129	< .000	0.048
Downside Deviation (annualized)	0.188	0.185	0.324	0.717	< .000	< .000
Panel C : One-factor model coefficients						
One-factor Alpha	-0.005	-0.004	-0.010	0.589	< .000	0.001
One-factor Beta	1.006	1.041	1.160	0.823	< .000	0.335
Panel D : Four-factor model coefficients						
Four-factor Alpha	-0.003	-0.002	-0.006	0.404	< .000	0.019
Four-factor Beta (Market premium)	0.902	0.804	0.977	0.729	0.008	0.234
Four-factor Beta (Size)	0.213	0.314	0.309	0.353	0.002	0.790
Four-factor Beta (HML)	0.176	0.200	0.211	0.711	0.563	0.810
Four-factor Beta (MOM)	-0.074	-0.058	-0.172	0.957	0.017	0.503
Panel E : Risk-adjusted performance measures						
Sharpe Ratio	-0.177	-0.022	-0.342	0.149	< .000	< .000
Treynor Ratio (one-factor beta)	-0.048	-0.006	-0.099	0.223	< .000	0.001
Treynor Ratio (four-factor beta)	-0.048	-0.021	-0.104	0.468	< .000	0.004
Sortino ratio	-0.247	-0.039	-0.406	0.162	< .000	< .000

The table reports the cross-sectional median for IG-i groups (stocks portfolio) and RG, on a per investor basis over the sample period. *,**,*** indicate that the difference is statistically significant at the level of 10%, 5% or 1%, respectively.

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ESSAYS ON EXCHANGE TRADED FUNDS AND RETAIL INVESTORS

YOUNES EL HICHOU EL MAYA

The evolution of online investing has been astonishing over the last two decades. More than ever, retail investors have their fate in their hands. They enjoy easy access to an extremely large variety of financial products which can sometimes be highly complicated and risky. To separate the wheat from the chaff, retail investors are left with limited resources in terms of skills, time, and wealth, and some of them opt for a passive investment strategy based on low-cost financial instruments, such as exchange-traded funds (ETFs). This doctoral dissertation consists of three essays about passive ETFs and retail investors using both trading records and survey-based data. The first essay shows that retail investors who trade passive ETFs are more sophisticated than those who do not. The second essay shows that passive ETF retail investors show different trading behaviors than individual stock investors. They have better understanding of diversification, have a larger portfolio size, lower turnover, hold their assets for longer periods of time and are less willing to trade lottery-like stocks. The third essay shows that heavy passive ETFs investors trade more passively. The portfolio total and systematic risks are lower for passive ETF investors, while risk-adjusted performance is negative but still higher than investors who trade individual stocks only.

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