Essays on investments in financial markets

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Short summary

In recent decades, financial markets have continued to evolve and potential investment products have multiplied. This expansion of products is particularly important against the background of the necessary private pension provision, because the demographic change, which affects the apportionment procedure in Germany, makes it almost impossible to fully finance retirement using public funds only. Additionally, very low interest rates in the euro zone since 2008 are the reason why formerly very popular and high-yield banking products can no longer generate positive outcomes. If private investors are looking for positive returns, capital market products offer a good opportunity.

This dissertation is about investment decisions of private investors with respect to different asset classes, macroeconomic influences and the economic development.

Chapter 1 deals with the reactions of German private investors to monetary policy decisions by the European Central Bank (ECB), in particular with regard to trading in equities and bonds. As a result, studies dealing with capital market reactions to monetary policy decisions are supplemented by the individual investor level. The investor reactions to these decisions are determined by the way of signaling, they change after the introduction of new signaling channels and in new situations such as the zero lower bound. It turns out that, above all, wealthier individuals are changing their positions on central bank decision days by buying products before the low-interest phase starts on days of expansive monetary policy decisions. In contrast, less sophisticated investors sell stocks after the onset of the crisis, which can be linked to higher media coverage.

Chapter 2 investigates the characteristics and investment decisions of German private investors in the trading of structured financial products. The investors who trade structured financial products are less risk averse, have a higher overall trading activity, and are more experienced in making investment decisions. While empirical studies generally show negative returns on these investments, this study shows that the trading motive is of crucial importance for profitability. Above all, transactions, with which existing portfolio positions are to be hedged, have negative returns. Investments made independently of the existing portfolio have positive returns before transaction costs.

In Chapter 3, the results of Campbell et al. (2010) and Schmittmann (2010) on hedge ratios in foreign currency investments are reviewed with a longer dataset over the period 1975 to 2016 and supplemented by a differentiation according to the business cycle. The optimal hedge ratios strongly depend on the target currency of an investment: although hedge ratios for investments

in euro-denominated products are smaller in recessions than in expansions, they are not significantly smaller than 1 for the majority of investors. Consequently, the euro cannot be classified as a reserve currency. By contrast, the Swiss franc and the US dollar continue to build on their reserve currency position during recessions, as their exchange rates are countercyclical to global equity markets.

Keywords: investment decisions; private household; financial markets; macroeconomic; financial innovation

Kurzzusammenfassung

In den letzten Jahrzehnten haben sich Finanzmärkte kontinuierlich weiterentwickelt und die möglichen Anlageprodukte haben sich vervielfältigt. Diese Ausweitung an Produkten ist vor allem vor dem Hintergrund der notwendigen privaten Absicherung für die Rente von hoher Bedeutung, da der demographische Wandel eine vollständige Finanzierung durch öffentliche Mittel nach dem Umlageverfahren in Deutschland kaum mehr ermöglicht. Hinzu kommt die seit 2008 anhaltende Situation sehr niedriger Zinsen im Euroraum, wodurch auch früher sehr beliebte und mitunter renditestarke Bankprodukte keine positive Verzinsung mehr anbieten können. Sind Privatanleger auf der Suche nach positiven Renditen, bieten Kapitalmarktprodukte eine gute Möglichkeit.

In dieser Dissertation geht es um Investitionsentscheidungen privater Haushalte im Hinblick auf verschiedene Anlageklassen, makroökonomische Einflüsse und konjunkturelle Gegebenheiten.

Kapitel 1 beschäftigt sich mit den Reaktionen deutscher Privatinvestoren auf geldpolitische Entscheidungen der Europäischen Zentralbank, insbesondere im Hinblick auf den Handel mit Aktien und Anleihen. Dadurch werden Studien, die sich mit Kapitalmarktreaktionen auf geldpolitische Entscheidungen befassen, um die Einzelinvestor Ebene ergänzt. Die Reaktionen hängen stark von der Art der Signalwirkung ab und ändern sich im Verlauf der Zeit mit unbekannten Signalen und Situationen wie der Niedrigzinsphase. Es zeigt sich, dass vor allem die wohlhabenderen Individuen ihre Positionen an Tagen mit Zentralbankentscheidungen verändern, indem sie vor dem Beginn der Niedrigzinsphase an Tagen mit expansiven geldpolitischen Entscheidungen Produkte kaufen. Dem gegenüber stehen Aktienverkäufe von weniger sophistizierten Investoren nach dem Beginn der Krise, die mit einer höheren Medienabdeckung in Verbindung gebracht werden können.

Das 2. Kapitel betrachtet die Eigenschaften und Investitionsentscheidungen deutscher Privatinvestoren beim Handel mit strukturierten Finanzprodukten. Investoren, die strukturierte Finanzprodukte handeln, sind weniger risikoavers, haben insgesamt eine höhere Handelsaktivität und sind geübter im Umgang mit Investitionsentscheidungen. Während empirische Studien im Allgemeinen negative Renditen aus Investitionen in diese Produkte zeigen, wird in dieser Studie deutlich, dass das Handelsmotiv von maßgeblicher Bedeutung für die Profitabilität ist. Vor allem Transaktionen, mit denen bereits bestehende Portfolio Positionen abgesichert werden sollen, haben negative Renditen. Investitionen, die unabhängig vom bestehenden Portfolio durchgeführt werden, haben positive Renditen vor Transaktionskosten.

In Kapitel 3 werden die Ergebnisse von Campbell et al. (2010) und Schmittmann (2010) zu Hedge Ratios bei Fremdwährungsinvestitionen mit einem längeren Datensatz über den Zeitraum 1975 bis 2016 überprüft und um eine Differenzierung nach dem Konjunkturzyklus ergänzt. Die optimalen Hedge Ratios hängen dabei stark von der Zielwährung einer Investition ab: Obwohl Hedge Ratios für Investitionen in Produkte, die in Euro notieren, in Rezessionen kleiner sind als in Expansionen, sind sie nicht signifikant kleiner als 1 für die Mehrheit der Investoren. Folglich spricht dies gegen die Einordnung des Euro als Reservewährung. Im Gegensatz dazu bauen der Schweizer Franken und der US Dollar ihre Stellung als Reservewährung während Rezessionen weiter aus, da sich ihre Wechselkurse antizyklisch zu globalen Aktienmärkten verhalten.

Schlüsselwörter: Investitionsentscheidungen; privater Haushalt; Finanzmärkte; Makroökonomie; Finanzinnovation

Abbreviations

BoE .... *Bank of England*

ECB..*European Central Bank*

ETF ....*Exchange Traded Fund*

HHI .... *Herfindahl-Hirschman-Index*

ISFP...*Investment Structured Financial Product*

LSFP ....*Leveraged Structured Financial Product*

MPC ....*Monetary Policy Committee*

SFP...*Structured Financial Product*

ZLB ....*Zero Lower Bound*

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Preface

The importance of capital market products is increasing steadily, especially against the background of insufficient public retirement provision because of the demographic change in Germany in combination with low levels of interest rates. For German private households who want to save for retirement, the usually used bank products, such as fixed deposits, can no longer yield high returns. Thus, after adjusting the small rewards from these savings products with the inflation rate, most of them yield a negative real return. That is why the focus of savers should shift towards capital market products, which still offer the chance of positive returns even in real terms.

Investors can choose between many different capital market products, of which equity and bonds are the most prominent ones. Their prices and returns are not only determined by corporation- or issuer-specific variables but they react significantly to changes of the main refinancing possibilities in an economy, which are guided by central banks. There are many studies pointing towards the relation between monetary policy and its effects on stocks and bonds (e.g. Bernanke & Kuttner (2005), Ehrmann & Fratzscher (2004), Bjørnland & Leitemo (2009)). Most of them agree with respect to the inverse relation between interest rates and stock or bond returns, which is based on the discount factor of future payments, and most pronounced for surprising monetary policy decisions. There are however inconsistencies when it comes to the direction of returns after the start of the financial crisis and the introduction of unconventional monetary policy instruments.

Chapter 1 called: *The impact of monetary policy on private investor trading* extends previous research by focusing on the investor perspective in connection with monetary policy, especially against the background of the financial crisis, and trading decisions. Using investor-fixed effects panel regressions, the impact of monetary policy decisions of the ECB between 1999 and 2015 on German private investors on a daily basis is examined. Differentiating for expected and unexpected monetary policy changes, the period of the financial crisis and the zero lower bound (ZLB), conventional and unconventional announcements, and investor sophistication and wealth, there is strong evidence for investor reactions to monetary policy. The direction of these trades depends on the time period and investor characteristics. The inverse relation found for capital markets holds for conventional decisions before the zero lower bound period, but it reverses afterwards. This suggests that investors react in line with theory and studies on capital market reactions as long as they are used to the way of signaling. While wealthy investors drive results of the whole group, buying with expansive monetary policy before interest rates approach the zero lower bound, unsophisticated investors leave the equity market in connection with monetary loosening after the start of the financial crisis. Relating this observation with media coverage on the ECB, the latter effect might be attention-based.

So far, the focus was on stocks and bonds as investment vehicles for private investors. One drawback of these products from a private investor perspective is the prohibition to enter short positions. This means, with these products households cannot benefit from negative or sideway moving markets. To overcome this problem, a new product class has been introduced in the 1990s, which is still growing in terms of its product diversity and importance. These are derivative products with a broad range of underlying securities, which are most often stocks, bonds, funds, commodity or exchange rates. These structured financial products enrich the product universe so that households can either secure their investments by buying products with a predefined minimum level of repayment (investment products), enter into short positions if they expect negative market movements or leverage the return of the underlying product in a positive or negative way to over proportionally participate in the development of the underlying (leverage products). Previous literature investigates the pricing of these products (e.g., Müller et al. (2017), Vokatá (2018)) and the returns of narrow product groups, and finds that, in general, they have negative outcomes (Entrop et al. (2016)). Chapter 2 expands this in that it takes into account not only some product categories but the whole group of leverage products. In addition, it evaluates performance in conjunction with the trading motives and the portfolio context.

Chapter 2 called: *Dissecting private investor performance and trading motives in innovative financial products* is joint work with Steffen Meyer and Lutz Johanning. Using a dataset on German retail investors who trade structured financial products between 2000 and 2015, we investigate their characteristics and performance in these products and in the portfolio context. Showing higher turnover, less risk aversion and higher portfolio values, investors using these products are more experienced and sophisticated. In general, investors generate small negative gross returns in leveraged structured financial products on the product level and in the portfolio context. Compared with other products, the returns are however less negative. Splitting investors based on their trading motives in these products shows that the negative performance stems from transactions that aim at hedging. Investors who use these products to accumulate wealth are able to generate positive returns before transaction costs.

Apart from investments in domestic currency, it is also possible to buy products in foreign currency, either to increase the portfolio diversification, to profit from speculation on the exchange rate development, or to decrease the overall risk of the investment portfolio by benefiting from correlations between international capital market products and exchange rates. Thus, investors need to decide how to deal with the exchange rate risk inherent in their positions, more specifically how their hedge ratios should be. Previous literature has focused on the risk minimizing properties and returns of different hedge ratios, spanning from simple ones with fixed ratios between 0 and 1 to more complex ones, which take into account the correlations between asset returns and exchange rates (e.g., Eun & Resnick (1988), Perold & Schulman (1988), Black (1989), Glen & Jorion (1993), Campbell et al. (2010), Schmittmann (2010)). The optimal hedge ratio depends on the home country of an investor and the investment destination. Currencies like the US dollar or the Swiss franc are considered safe haven currencies, which means that they negatively correlate with international asset returns. Therefore, from a risk-minimizing perspective, it is optimal to hold open positions in these currencies. Lately, studies discussed the state of the euro as a safe haven currency as well, whereby the prominent studies of Campbell et al. (2010) and Schmittmann (2010) generate diverging results. That is why chapter 3 focuses on reassessing the methods of these two base studies with an extended sample period.

Chapter 3 called: *Business cycle variations in exchange rate correlations: Revisiting global currency hedging* is joint work with Steffen Meyer and Jantke de Boer and is published in *Finance Research Letters* (2020, Volume 33, Article 101195). Applying the analyses of Campbell et al. (2010) and Schmittmann (2010), we revisit their main findings covering an extended period from 1975 to 2016 and add a business cycle split. While we can confirm most of the results in the extended sample period, the progress of the euro in becoming a reserve currency vanished during the financial crisis. Even though hedge ratios of investments in euros decrease during recessions compared with expansions, they are not significantly smaller than 1 for the majority of investors. In contrast, the Swiss franc and US dollar enhance their status as safe haven currencies during recessions, as their exchange rates move anti-cyclically with global stock markets. Our results provide evidence for the risk management properties of currencies for financial institutions, especially during different business cycle phases, to enhance welfare.

Chapter 1: The impact of monetary policy on private investor trading

1.1 Introduction to Chapter 1

Monetary policy has important implications for all subjects in an economy. It signals the intended future path of the economic development by improving or constraining the possibilities to refinance. One important transmission channel of monetary policy is the capital market, where a change in the level of interest rates determines, among others, the attractiveness of equity compared with fixed income securities. Given, that the value of investments in these securities affects the amount of money available for spending, as well as investors' creditworthiness (Mishkin (2001)), investors are likely to react to monetary policy announcements and to rebalance their portfolios according to the changes in expectations.

This relation is not only of interest for researchers but also ranks high on the agenda of policy makers as ECB-president Draghi states: *"In particular, there have been concerns that very low rates for a prolonged period might penalise savers to the benefit of debtors; or that rising asset prices as a consequence of our purchases might benefit the wealthy disproportionately and thereby increase inequality"* (Draghi (2015)).

Apart from very long-term effects on the financial attitude (Malmendier & Nagel (2011)), there is a surprising lack of literature that looks at the reactions of private households on capital markets in the context of monetary policy.

Taking into account past literature on investment decisions of private investors, results show that they do not act completely in line with what theoretical and empirical models would suggest. Some of the most undesirable observations about their investment behavior are overconfidence, which leads to excessive trading (e.g., Lewellen, Lease, & Schlarbaum (1980)) and the disposition effect – an effect that stems from the refusal to admit a previous mistake – (e.g., Shefrin & Statman (1985)), home bias (e.g., Tesar & Werner (1995)) and overreacting to surprising and extreme news events (e.g., De Bondt & Thaler (1985), Kormendi & Lipe (1987), Kim & Verrecchia (1991), Barber & Odean (2008), Engelberg & Parsons (2011)). However, the severity of these biases can depend on some investor characteristics, such as their sophistication and wealth (e.g., Campbell (2006), Guiso & Sodini (2012)), where higher levels lead to decisions that are more rational.

While past literature on private investor trading does not investigate immediate reactions to monetary policy decisions, capital market reactions are analyzed in several dimensions. Previous studies on this relation apply event studies and reveal highly comparable results that are generally in line with stock pricing theory: expansive (restrictive) monetary policy causes rising (declining) stock prices on the announcement day (e.g., Ehrmann & Fratzscher (2004), Rigobon

& Sack (2004), Bernanke & Kuttner (2005), Bjørnland & Leitemo (2009)), especially in a normal economic environment. In line with the efficient market theory (Fama (1970)), markets react stronger to monetary policy announcements if these decisions are not anticipated. Surprisingly, this evidence is not consistent over time. The directions of these effects change after the start of the financial crisis. While some studies detect a weakening of conventional policy effects (Hosono & Isobe (2014)), others even highlight a reversal of stock price reactions (Gregoriou et al. (2009), Kontonikas, MacDonald, & Saggu (2013), Florackis, Kontonikas, & Kostakis (2014)). A growing body of literature now also examines the effects of unconventional monetary policy during the financial crisis (keeping the main interest rate constant but expanding the monetary base) on the bank-lending channel, interest rates and spreads as well as macroeconomic variables. A large portion of these studies supports the effectiveness of unconventional policy in affecting and improving macroeconomic conditions,[1] even though some researchers negate the intended impact or show that it is only transitory (Wright (2012), Gambacorta, Hofmann, & Peersman (2014), Acharya et al. (2016)).

As the effects on capital markets are very strong, investors who participate in them ought to be highly affected as well. To investigate this relation, the analysis in this paper focuses on the abnormal trading behavior of German private investors in response to monetary policy decisions of the ECB between 1999 and 2015. This is implemented in an event study setting and using investor-fixed effects panel regressions for every individual investor. Daily excess buy-sell imbalances for both the number of transactions and their value in euros generate the excess trading of the private investors in connection with the monetary policy decisions.

Apart from the effects on all securities as a homogenous group, changes in the portfolio composition are investigated by splitting for equity and fixed income securities. Additionally, there are analyses for a subset of wealthy (measured by their portfolio value) and sophisticated investors based on the degree of diversification in their portfolios measured by the Herfindahl-Hirschman-Index (HHI) (Calvet, Campbell, & Sodini (2009a)).

Following the literature on stock market reactions to monetary policy announcements, these decisions are classified as being expected changes, unexpected changes or unconventional announcements (cf. Haitsma, Unalmis, & de Haan (2016)). As the sample period covers several market phases, it is split into ordinary times, crisis times and periods, in which interest rates are close to the zero lower bound.

[1] Cf. Kashyap & Stein (2000), Curdia & Woodford (2011), Hancock & Passmore (2011), Wu (2011), Chung et al. (2012), D'Amico et al. (2012), Giannone et al. (2012), Joyce & Tong (2012), Kapetanios et al. (2012), D'Amico & King (2013).

The data on private investors stem from an online brokerage and include information on every self-initiated trade (excluding any automated trading, such as savings-plans or limit orders, and advised transactions) that took place in the sample period. The analyses control for investor-fixed effects, market-wide effects by including returns of the CDAX, national holidays, day-light-savings, first and last day of the week and the month, days at which exchanges are closed, and month- and year-fixed effects.

This results in the following major findings: monetary policy actions catch private investors' attention and lead to significant reactions in the direction of their trading. For conventional decisions from 1999 to the beginning of the financial crisis in 2007, the inverse relation found for capital markets also holds for private investors. As expected, private investors react to monetary policy decisions quite rationally as long as they are used to the way of signaling.

In contrast, unconventional announcements during the crisis and conventional announcements near the ZLB reveal a change in coefficients. Investors no longer enter the market on expansive signals but rather exit. This means, they might be interpreting these announcements as signals of a weak economic situation or an increase of uncertainty. A period of rates at the ZLB is completely new to markets and investors. This might be the reason why the normal signaling channels do not work the way they used to. The same rationale is true for unconventional monetary policy, which has never before been implemented in the euro area. With rates at the ZLB, the announcement of unconventional policy affects investors in the intended direction again. This rather speaks to investors having faith in the ECB's ability to stabilize financial markets, than to an understanding of the expansive nature of these interventions. The documented effects are mainly driven by sophisticated and wealthy investors.

The rest of the paper is structured as follows: Section 1.2 contains the identification strategy. The general approach is an event study on the individual investor level, where trading variables of sample investors are defined to be excess measures in terms of purchases and sales. In addition to the definition of monetary policy variables based on different time periods, control variables and sample splits are introduced. Sections 1.3 and 1.4 cover the datasets of private investor trading and monetary policy actions and a discussion of the results. Section 1.5 concludes.

1.2 Identification strategy

1.2.1 General approach

The approach applied is in general an event study comparable to literature on capital market reactions to monetary policy.[2] However, instead of using market returns, investor trading is the variable of interest on the left hand side of panel regressions with investor-fixed effects. As previous literature shows, results of event studies based on daily data are unbiased due to the sufficiently short time interval and immediate reactions in line with efficient market theory (Gürkaynak, Sack, & Swanson (2005), Swanson, Reichlin, & Wright (2011), Kontonikas, MacDonald, & Saggu (2013)).

The analyses examine the abnormal trading by the private investors on and around monetary policy events, which are defined as the meeting days of the Governing Board of the ECB followed by press conferences. Opposite to previous event studies on real effects of monetary policy, instead of looking at stock market returns, this analysis tries to explain private investor trading with monetary policy events on the event days. In general, the following regression is estimated:

$$PIT_{i,t} = \alpha + \beta_{i,t} MP_{i,t} + C_{j,t} + \varepsilon_t, \tag{1.1}$$

where the abnormal trading of the private investors ($PIT_{i,t}$) on meeting days of the Governing Council of the ECB ($MP_{i,t}$) is compared to the normal trading behavior of the same investor controlling for additional sets of variables (investor related variables, calendar dates, month- and year-fixed effects) $C_{j,t}$.[3] Heteroskedasticity-robust standard errors are computed. However, results remain unaltered if clusters for the individual investor are included instead. Table A 1.1 in the appendix gives an overview of all of the variables described in the subsequent paragraphs.

1.2.2 Trading variables

The trading variables of private investors ($PIT_{i,t}$) are defined as the daily abnormal trades by individuals. To do so, excess buy-sell measures per investor including all securities traded by private investors in the sample are calculated in the following way:

$$ExBS^{\#} = \frac{Buy^{\#}_{i,t}}{Buy^{\#}_{i,t} + Sell^{\#}_{i,y}} - \frac{Buy^{\#}_{i,y}}{Buy^{\#}_{i,y} + Sell^{\#}_{i,y}}, \tag{1.2}$$

[2] Running an event study in the style of Bernanke & Kuttner (2005), regressing on meetings days only instead of all days, does not qualitatively alter the results.
[3] Additional tests investigate the relationship on one day prior to and after the monetary policy meeting day but the strongest effects are found on the meeting day itself. Therefore, results of the other regressions are not included.

$$ExBS^{EUR} = \frac{Buy_{i,t}^{EUR}}{Buy_{i,t}^{EUR} + Sell_{i,y}^{EUR}} - \frac{Buy_{i,y}^{EUR}}{Buy_{i,y}^{EUR} + Sell_{i,y}^{EUR}}. \tag{1.3}$$

This methodology is based on Schmittmann et al. (2014). Both equations show excess buy-sell imbalances of a single investor defined as the excess buy-sell imbalance of individual investor i on day t relativized with this investor's average buy-sell imbalance of the corresponding year y. While Equation (1.2) measures the buy-sell imbalance in terms of the number of transactions, Equation (1.3) takes into account the monetary value of these transactions. This distinction of trading variables is necessary to prevent biases in the estimation, which might otherwise result from few very big transactions (monetary value of transactions) or a large number of very small trades (number of transactions) that may be too small in value to be economically relevant.

1.2.3 Monetary policy variables

The Governing Board of the ECB meets at regularly scheduled time intervals eight times per year to decide on the monetary policy stance of the euro area based on the economic situation. Previous studies on the capital market effects of monetary policy show significant changes in the prices of securities on the days these meetings take place. In line with the theory on market efficiency, those prices react more strongly if the policy decision was not anticipated. In order to account for the degree of anticipation on financial markets, three-month futures contracts on the Euribor are applied.[4] The surprise component of a conventional interest rate change is therefore:

$$\Delta r_t^u = \quad f_{t+1}^0 - f_t^0, \tag{1.4}$$

where f_{t+1}^0 represents the current month futures spot rate the day following a policy decision and f_t^0 stands for the futures rate on the event day.[5] This combination of rates is necessary when investigating the euro area because the Euribor rate is disclosed at 11:00 CET but meetings of the Governing Council of the ECB do not start before 13:45 CET. As a consequence, futures rates cannot reflect interest rate changes until the next day.

At the same time, expected interest rate changes are the difference between the actual change and the unexpected one:

$$\Delta r_t^e = \quad \Delta r_t - \Delta r_t^u. \tag{1.5}$$

[4] The first ones to reveal the possibility to use futures contracts in order to account for anticipation of monetary policy decisions were Cook & Hahn (1989). A later study of Kuttner (2001) supports this method.
[5] To calculate futures rates, the daily settlement price is subtracted from 100.

As the sample period under investigation spans from 1999 to 2015, it includes different phases of monetary policy. The policy decisions described so far can be defined as being "conventional"; they take place at regularly announced meeting days including either changes of the main refinancing rate or press conferences without any rate change. This holds for every decision prior to the start of the crisis but there are several of these policy days during the crisis as well.

In contrast to the conventional decisions, unconventional changes are those that give signals apart from adjustments to the main refinancing rate. Specifically, these instruments are either asset purchase programs or liquidity provisions. They were established during the financial crisis only, which is defined in this study to start with the first unconventional policy announcement on 22 August 2007.[6] In order to detect to what degree an unconventional decision is anticipated, Rogers, Scotti, & Wright (2014) introduce the change in the spread between the 10-year government bond yield of Italy and Germany. The unconventional surprise $\Delta r_t^{u,c}$ can be represented by:

$$\Delta r_t^{u,c} = \left(y_{s,t}^I - y_{s,t}^G\right) - \left(y_{s,t-1}^I - y_{s,t-1}^G\right). \tag{1.6}$$

An increase in this spread implies that the monetary policy decision is tighter than expected and vice versa. The underlying rationale is the aim to reduce the intra euro area yield spread (Rogers, Scotti, & Wright (2014)).

After defining these two sorts of policy decisions (conventional and unconventional), the particularity of the sample period allows us to investigate several effects. The sample is split in three periods:

1) Pre-crisis: 1 January 1999 to 21 August 2007
2) Crisis: 22 August 2007 to 4 July 2012
3) Zero Lower Bound: 5 July 2012 to 31 December 2015.

After the meeting of the 5th of July 2012, the rate of the deposit facility hit the 0% boundary, meaning banks no longer got a positive interest rate on their overnight deposits with the ECB. Since there is no other common definition, this date marks the beginning of the ZLB period.

All of the previously defined variables on specific monetary policy actions are represented by $MP_{i,t}$. Using dummies for the different periods results in eight monetary policy variables.[7]

[6] This definition of the start of the crisis follows Haitsma, Unalmis, & de Haan (2016).
[7] To recap, take a look at Table A1.1.

1.2.4 Control variables

The regressions include several sets of control variables ($C_{j,t}$) to account for market effects that have already been found in previous research.

1. Investor related effects

Some previous studies show that private investors take into account preceeding stock market returns when deciding on their investments (e.g. Grinblatt & Keloharju (2001), Barber & Odean (2008)) or react to information with a small delay (Garcia (2013)). To account for this evidence, three momentum variables on the German CDAX that consider the one-day market return of the previous day, the squared previous-day return and the market return of the previous three months are included.

Wealth differs significantly between individuals in this dataset. Therefore, it might be possible that some very large trades of extremely wealthy individuals or changes in the wealth of investors over time distort the overall results. The natural logarithm of the aggregated amount of all assets an investor holds at the end of the previous month is added in order to eliminate this problem.

2. Calendar dates

Other market anomalies focus on certain days of a trading year. Both vacations and national holidays might influence the willingness to trade. Thus, the analyses include variables for the last trading day before vacations and the first trading day afterwards. Likewise, there are control variables for one trading day before a national holiday, the holiday itself and one trading day after the public holiday.

Furthermore, German investors probably trade predominantly on German exchanges. Every day they are closed, the trading volume drops significantly which is why these days are controlled for as well.

As previous studies show, capital market returns follow specific paths if there is a change of year or of month, and for specific days of a week (Lakonishok & Smidt (1988), Lakonishok & Maberly (1990)). To take these observations into account, it is worthwhile to control for the first and the last day of a month and a year as well as for Mondays and Fridays.

Daylight savings can strongly influence the human biorhythms, see for example Kamstra, Kramer, & Levi (2003). Dummy variables for Mondays after a change in the daylight saving time account for these effects.

3. Fixed effects

The last set of control variables includes month- and year-fixed effects. Over a course of 17 trading years, the trading activity of investors can differ significantly. Also, the period of the financial crisis and the following ZLB phase might affect the investment decisions particularly. To find out about the trading behavior of private investors on monetary policy days, the overall economic situation that changes over time along with other slow-moving seasonal effects should not drive the results. Year-fixed effects are one way to mitigate this concern.

Within a trading year, different months reflect particular trading behavior. A possible reason for this observation are tax-driven motives that come into play at the end of a year. Hence, dummies for every month are included as well.

1.2.5 Sample splits

1. Asset class

In investigating the channels of monetary policy, Florackis, Kontonikas, & Kostakis (2014), examine market reactions to monetary policy of the Bank of England during the financial crisis and state: "*Interest rate cuts during the crisis not only failed to boost stock prices at MPC [Monetary Policy Committee] meeting days, but they actually led liquid stocks to lower prices because these were perceived by stock market participants as bad news, signals by the BoE [Bank of England] of a worsening economic outlook. Second, and related to the previous point, interest rate cuts during the crisis reinforced "flight to safety" trading away from declining stocks and towards government bonds.*" (Florackis, Kontonikas, & Kostakis (2014, p. 4)) This suggests that investors perceive these expansive policy decisions to be rather a sign of the bad economic situation, which makes them fear the equity market. Instead, they hope to secure their money in the bond market that offered lower returns in the past but at the same time the feeling of higher safety. A differentiation for equity and fixed income securities is applied to investigate whether this evidence also holds for trading of German private investors. A table of security properties provided by the bank partnering contains information on whether a particular security is an equity or a fixed income instrument. Balanced funds are assumed to be an equity security with a weight of 70% and a fixed income security with a weight of 30%.

2. Investor characteristics

Several studies on household finance find trading characteristics to differ between certain subgroups of individuals. One important determinant of investment decisions is the sophistication. Tan, Ying Wang, & Zhou (2014) reveal that the sophistication determines significantly the way an investor reacts to certain news. While the sophisticated investors are able to interpret the announcements and disclosures correctly, adjusting their trading subject to the information they read between the lines, the unsophisticated investors consider the news as a fact. Da, Engelberg, & Gao (2011) give supporting evidence showing that especially the rather unsophisticated investors increase their trading. Further literature (Dhar & Zhu (2006), Kimball & Shumway (2010), Seru, Shumway, & Stoffman (2010), Guiso & Sodini (2012)) also shows that investment mistakes emerge less if an investor is rather sophisticated.

As stated by Feng & Seasholes (2005, p. 309): "*After all, the number of stocks is a measure of sophistication as it shows the desire to diversify*." Using the diversification in an investor's portfolio at the end of each trading month (Calvet, Campbell, & Sodini (2009a)), the HHI measures the amount of concentration. A highly diversified portfolio does not show any concentration, therefore the index is close to zero. In contrast, a portfolio with very few different single assets is highly concentrated, which is demonstrated by a HHI close to one. Subject to the average index value over all monthly values, investors are grouped into deciles of which the first one shows the smallest concentration. Low concentration suggests that investors are highly diversified and therefore are rated as sophisticated. In order to split the sample with respect to the sophistication, only the first four deciles showing the least concentration are considered to be "sophisticated", the rest is considered to be "unsophisticated".

To investigate the potential distributional effects mentioned in the introductory Draghi speech and also shown in previous research, for example worsening investment mistakes with lower wealth (Campbell (2006)), investors are also split subject to their wealth. Individuals are defined to be "wealthy" if their average monthly portfolio value exceeds the median of the portfolio values for the majority of months. Conversely, individuals whose wealth is most often below that threshhold are considered to be "less wealthy". The resulting split deviates from a simple split at the median to avoid outliers in the data.

1.3 Data

The data needed in order to apply the previously described methodology consist of two parts, one contains all trading characteristics of the retail investors of a large German brokerage and the other one includes information on the monetary policy decisions and meetings of the ECB. The sample period starts in January 1999, with the beginning of the ECB mandate, and ends in December 2015.

During the whole sample period, there are 220 meetings of the Governing Council of the ECB but only some of them include actual changes of the monetary policy stance. The conventional decisions dominate as they take place almost monthly during the entire period. These conventional meetings lead to 40 rate changes. While the main refinancing rate is increased in 18 of the cases, it diminishes 22 times. Mostly, the modifications are small amounting to 0.25 percentage points, eleven of the changes alter the main refinancing rate by 0.5 percentage points and within the crisis, one adjustment has a value of -0.75 percentage points. The last two actual rate changes of the sample period decrease the main interest rate each with by 0.1 percentage points, leading to an interest rate level of 0.05%. In addition, the unconventional decisions taking place during the crisis (beginning with the first unconventional monetary policy meeting on 22 August 2007) amount to 19 announcements and reflect only expansionary monetary policy since they aim at providing the economy with money.

Table 1.1: Number of monetary policy decisions by type and period

This table shows the number of observations per type of monetary policy decision split into the three phases pre-crisis, crisis and ZLB. The conventional monetary policy decisions are divided into an expected and a surprising part each of which can be either more or less expansive or restrictive than expected. Expectations are included by using three-month futures on the Euribor (Cook & Hahn (1989), Kuttner (2001)). Numbers < 0 suggest monetary loosening, whereas those > 0 represent tighter policy. Even though the unconventional decisions themselves are exclusively expansive, the degree can differ subject to anticipation in capital markets. Therefore, following Rogers, Scotti, & Wright (2014) the level of anticipation is measured by computing the change in the 10-year spreads of the yields of sovereign bonds of Italy and Germany before and after the unconventional decision.

	Observations in monetary policy decisions					
	Expected Conventional		Unexpected Conventional		Unexpected Unconventional	
	< 0	> 0	< 0	> 0	< 0	> 0
Pre-Crisis	71	61	55	66	--	--
Crisis	28	30	31	24	9	4
ZLB	18	12	13	11	5	1

However, as the main interest lies on the anticipated or surprising parts of these decisions, Table 1.1 shows the direction of the policy decisions when taking into account the anticipation. This way, the actual announcement is compared with the expectation and the resulting numbers display whether the policy decision is more or less expansive or restrictive than expected, irrespective of the actual direction or an absence of rate changes. The differentiation between expansive and restrictive measures shows that the number of these changes is comparable for conventional monetary policy decisions. In contrast, the majority of unconventional decisions is more negative, which means these decisions are more expansive than expected.

The investor data come from a large German online brokerage. From the several hundred thousand clients the brokerage serves, the focus lies on a randomly drawn sample of roughly 82,000 investors who held a customer account within the period ranging from 1999 to the end of 2015 and traded at least once every year of this period. Excluding all investors who use financial advice and all transactions that stem from automated trading, such as savings-plans or limit orders, results in transactions, which are based on a particular decision of an individual investor. Hence, an individual investor exclusively initiates every transaction.

The sample investors make about 34.7 million trades, with a transaction value of 211.2 billion euros. For all the trades, 54 % are purchases (approximately 18.9 million trades and 113 billion euros), whereas 46 % are sales (approximately 15.8 million trades and 98.2 billion euros).

As Table 1.2 Panel A shows, the average age of investors is 54 and the median age is 52. 18.1% of the sample is female and 81.9% is male. The average portfolio value amounts to 59,300 euros whereas the median is significantly smaller with 34,400 euros. Comparing this mean value with official statistics of Deutsche Bundesbank (2013) reporting the average portfolio value of a German stock market investor to be around 48,000 euros, the sample value is significantly bigger. Thus, it is even more unlikely for these accounts to be solely play money accounts.

Panel B and C differentiate for the sophistication of investors by their values of the HHI. While the sample sizes of these subsamples differ considerably, leaving only 30% of the investors in the sophisticated group, the dimensions of the other variables are very similar. The share of female investors increases in the sophisticated group whereas the average portfolio value is almost indistinguishable from the unsophisticated ones. In contrast, a split for portfolio value in Panel D and E results in more diverging numbers. With a mean age of 56, wealthy investors are considerably older than less wealthy ones, whose average age is 50 years. The average portfolio value differs extensively by definition. For wealthy investors it is 5 times the value of the less wealthy ones. In contrast, the share of female investors is very similar in both groups. The number of investors in these two subgroups is similar but not equal due to the allocation method used to form the groups.

Table 1.2: Private investor characteristics

This table shows the properties of the private investors in this sample for the variables age, gender and average portfolio value. Panel A displays the characteristics for all investors in the dataset, which amount to almost 82,000 individuals. Panels B and C split the investors subject to their sophistication measured in terms of their portfolio diversification based on the HHI. The sophisticated investors show a HHI value below 5, the unsophisticated ones are characterized by values above 4. Panels D and E split for the wealthiness of investors where individuals are defined "wealthy" if their average monthly portfolio value exceeds the median of portfolio values in the majority of months and less wealthy if it is below.

	Mean	Standard Deviation	Median	Observations
Panel A: All Investors				
Age (in years)	53.84	12.84	52	81,980
Gender (Male, in %)	82.0%	38.4%	1	81,980
Average Portfolio Value (in €)	59,347	119,231	34,439	81,980
Panel B: Sophisticated Investors				
Age (in years)	52.47	12.75	51	24,167
Gender (Male, in %)	76.7%	42.3%	1	24,167
Portfolio Value (in €)	58,899	127,537	32,928	24,167
Panel C: Unsophisticated Investors				
Age (in years)	54.41	12.84	53	57,813
Gender (Male, in %)	84.2%	36.5%	1	57,813
Portfolio Value (in €)	59,535	115,583	35,041	57,813
Panel D: Wealthy Investors				
Age (in years)	56.55	12.96	55	43,123
Gender (Male, in %)	82.9%	37.7%	1	43,123
Portfolio Value (in €)	95,070	154,081	61,650	43,123
Panel E: Less Wealthy Investors				
Age (in years)	50.83	12.01	49	38,857
Gender (Male, in %)	81.0%	39.2%	1	38,857
Portfolio Value (in €)	19,703	25,644	14,898	38,857

1.4 Results

1.4.1 General findings

Starting with the results on excess buy-sell imbalances of all sample investors around monetary policy decisions of the ECB, Table 1.3 shows the coefficients for a combined regression of all policy variables and periods. By including the previously defined control variables and fixed effects, it seems that the trading behavior of private investors is not consistent over time and differs in terms of the policy decision. The table shows trading in all securities, both for the number and the value in euros of transactions.

While the coefficients are positive with only a small statistical significance under unexpected policy decisions in the pre-crisis period, investors react in an inverse way to expected ones.

Interpreting this result, an expected rate decrease that takes place before 22 August 2007 causes security purchases by individual German investors. This way, they align their trading decision in accordance with capital market reactions. In contrast to studies on capital market reactions, we find that individual investors react significantly more on expected changes in the monetary policy.

Table 1.3: The effect of monetary policy on the average investor

This table shows the results of investor-fixed effects panel regressions on the trading behavior on meeting days of the Governing Board of the ECB for an average investor. The abnormal trading is measured by excess buy-sell imbalances, which relativize trading on meeting days with "normal" trading of the corresponding year. The excess buy-sell imbalances are measured in terms of the number of transactions ("#") and the monetary value ("EUR"). There are three different variables that account for monetary policy decisions of the ECB ("expected change", "conventional surprise" and "unconventional surprise") between 1999 and 2015 differentiating for three periods: "Pre-Crisis" (before the start of the crisis on 22 August 2007), "Crisis" (after 22 August 2007 but before rates hit the zero lower bound on 5 July 2012) and "ZLB" (rates at the zero lower bound starting 5 July 2012). All control variables are included in each regression. p-values based on heteroskedastic-robust standard errors are reported in parentheses. Note: ***, **, * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	All Securities	
	#	EUR
Normal Market Period (Pre-Crisis)		
Conventional Surprise	0.0240*	0.0271*
	(0.0145)	(0.0147)
Expected Change	-0.0629***	-0.0552***
	(0.0186)	(0.0190)
Crisis Period		
Conventional Surprise	-0.128***	-0.170***
	(0.0306)	(0.0315)
Expected Change	-0.0697**	-0.116***
	(0.0355)	(0.0365)
Unconventional Surprise	0.0271***	0.0285***
	(0.00520)	(0.00535)
Zero Lower Bound Period		
Conventional Surprise	1.122***	0.991***
	(0.147)	(0.154)
Expected Change	1.432***	1.246***
	(0.185)	(0.193)
Unconventional Surprise	-0.0139***	-0.0151***
	(0.00328)	(0.00339)
Controls	YES	YES
Year-Fixed Effects	YES	YES
Month-Fixed Effects	YES	YES

Comparing this finding with the coefficients of the crisis period but before rates hit the ZLB, both kinds of conventional policy decisions cause the same directional effect: decreasing interest rates lead to security purchases. Since the period of the crisis is characterized by a sharp fall in interest rates, on announcement days about these decisions, investors increase their portfolio value by buying securities. During the crisis, there are not only conventional announcements on interest rate changes but also unconventional ones, which alter the monetary base. These seem to have the opposite effect in terms of investor trading. If an unconventional decision is more expansive than expected, households decrease their demand for securities. Thus, while the conventional expansive policy during the crisis period serves as a positive signal causing the same inverse reaction as the one also found to hold for capital markets, unconventional decisions are interpreted in the opposite way by the investors.

Near the ZLB, there is a reversal of the investor reactions for both conventional and unconventional policy as compared to the period before. The positive relation found for unconventional decisions before the ZLB period can now be observed for both kinds of conventional ones with rates close to zero. However, unconventional decisions now show the expected inverse relation with investors purchasing if the policy announcement is more expansive than expected. These results are robust to using the value in euros or the number of trades.

Given that capital markets react to the decisions in an inverse manner, an inverse reaction of the private households would have been expected as well. However, this direction can only be observed for the conventional decisions before interest rates approach the ZLB. This way, the intended idea of expansive policy to improve the economic conditions seems to be understood by households: investing in capital markets in expectation of rising prices should further stimulate and lead to positive returns. In contrast, unconventional policy before the ZLB and conventional decisions at the ZLB show positive coefficients. Thus, monetary policy does not send the same signal to individual investors as before, even though the signaling methods themselves do not alter under conventional rate changes. This suggests that investors also take into account other factors when adjusting their portfolios to monetary policy announcements, for example the economic environment, their personal economic expectations or the aggregate economic uncertainty.

Remarkably, private investors trade stronger following expected changes than on surprising ones. This contradicts not only capital market efficiency but also the previous studies on capital market reactions to monetary policy and household behavior related to news (e.g. Engelberg &

Parsons (2011)). This might suggest that private investors do not monitor monetary policy decisions of the ECB in advance – otherwise, they should have been aware of the expectation and would not trade on it – but rather act on an announcement as it becomes public.

Given market level evidence on investors substituting equity with bonds (Florackis, Kontonikas, & Kostakis (2014)), Table 1.4 shows the results of trading in equity and fixed income securities by the private investors. The purchase transactions found in the overall results for expected expansive changes before the start of the crisis take place predominantly in equity securities. This suggests that the expected part of expansive policy before the start of the crisis contains a strong signal of improving economic conditions, potentially in combination with the expectation of raising inflation.

In contrast, coming to the second part of rows of Table 1.4, which shows coefficients for the financial crisis, the direction of abnormal equity trading has reversed. In this period, all kinds of announcements of an expansive conventional policy decision, either expected or surprising, cause a significant decline of purchases of equity both for the number and the monetary value of transactions. In line with the results of Florackis, Kontonikas, & Kostakis (2014), there seems to be a shift from equity to fixed income securities with expansive conventional policy, even though the coefficients of the latter are not statistically significant. This replacement strengthens the hypothesis of a "flight-to-safety", where investors lose trust in equity markets but not in fixed income securities. The opposite is true when looking at unconventional policy during the crisis: these coefficients are positive, suggesting a market exit strategy for both kinds of asset classes with expansive policy that might be driven by an overall weakening economic situation.

Table 1.4: The effect of monetary policy on the average investor differentiating for asset classes

This table shows the results of investor-fixed effects panel regressions on the trading behavior on meeting days of the Governing Board of the ECB for an average investor. The abnormal trading is measured by excess buy-sell imbalances that relativize trading on meeting days with "normal" trading of the corresponding year. The excess buy-sell imbalances are measured in terms of the number of transactions ("#") and the monetary value ("EUR"). Investigating trading in equity and fixed income securities separately enables to account for different transmission channels of monetary policy. There are three different variables that account for monetary policy decisions of the ECB ("expected change", "conventional surprise" and "unconventional surprise") between 1999 and 2015 differentiating for three periods: "Pre-Crisis" (before the start of the crisis on 22 August 2007), "Crisis" (after 22 August 2007 but before rates hit the zero lower bound on 5 July 2012) and "ZLB" (rates at the zero lower bound starting 5 July 2012). All control variables are included in each regression. p-values based on heteroskedastic-robust standard errors are reported in parentheses. Note: ***, **, * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	Equity		Fixed Income	
	#	EUR	#	EUR
Normal Market Period (Pre-Crisis)				
Conventional Surprise	0.0265*	0.0288*	0.260**	0.249**
	(0.0154)	(0.0156)	(0.118)	(0.119)
Expected Change	-0.0897***	-0.0882***	0.0466	0.0635
	(0.0203)	(0.0207)	(0.140)	(0.146)
Crisis Period				
Conventional Surprise	0.0970**	0.0949**	-0.121	-0.101
	(0.0421)	(0.0431)	(0.195)	(0.198)
Expected Change	0.107**	0.0869*	-0.273	-0.283
	(0.0478)	(0.0491)	(0.221)	(0.226)
Unconventional Surprise	0.0806***	0.0864***	0.212***	0.222***
	(0.00681)	(0.00697)	(0.0237)	(0.0243)
Zero Lower Bound Period				
Conventional Surprise	0.363	0.321	-2.090***	-2.123***
	(0.222)	(0.227)	(0.791)	(0.803)
Expected Change	0.957***	0.818***	-1.356	-1.366
	(0.278)	(0.284)	(0.984)	(1.000)
Unconventional Surprise	-0.0192***	-0.0172***	0.0199	0.0178
	(0.00484)	(0.00494)	(0.0165)	(0.0170)
Controls	YES	YES	YES	YES
Year-Fixed Effects	YES	YES	YES	YES
Month-Fixed Effects	YES	YES	YES	YES

Turning to trading close to the ZLB, the effects of conventional monetary policy remain unaltered. For both expected and unanticipated expansive decisions, the investors sell equity in exchange for fixed income securities. The size of the excess-buy-sell imbalances for fixed income securities with conventional surprises is puzzling but might be explained by the following rationale. The perception of the economic situation worsens in as much as stocks become even less attractive but fixed income securities are still considered sufficiently safe and/or investors believe that euro zone government bonds have a smaller probability of defaulting than the market expects. Thus, investors might speculate on a high yield, which is hardly available elsewhere during that time, while feeling sufficiently safe subject to the protection of bailouts of the European Union or the International Monetary Fund.

1.4.2 Findings sorted by investor characteristics

To see how trading patterns might differ for subsamples based on the investor characteristics wealth and sophistication, which are essential for analyses taking into account distributional effects, Table 1.5 starts by focusing on the trading activity of investors divided by their level of sophistication. Sophisticated individuals are defined by the lowest four deciles (Panel A) and unsophisticated ones by the highest six deciles of portfolio concentration (Panel B) measured by the HHI.

Comparing the two groups of investors divided by their sophistication, the first two columns covering all securities show that the more sophisticated ones pay attention before the start of the crisis and trade on days of monetary policy meetings while the unsophisticated ones hardly react at all prior to 2007. After the start of the financial crisis, both subsamples have quite similar coefficients. Only in case of unconventional surprises at the ZLB, the unsophisticated investors trade more. Coming to the columns on the right side, which contain trades in equity and fixed income securities, there is evidence that the unsophisticated investors react by selling equity to all expansive policy announcements after the start of the crisis, a reaction consistent with a flight from the equity market. In contrast, there is no clear pattern for similar transactions of the sophisticated investors.

This observation might suggest an attention-driven effect of the unsophisticated subgroup of investors, which seems to be rooted in an increase of media attention. At first glance, Figure 1.1 shows an increase of media coverage on articles about the ECB with decreasing interest rates. Media coverage is measured by counting the number of digital newspaper articles in LexisNexis that mention the German word “EZB” (in English “ECB”) in their headlines.

Subsample regressions controlling for autocorrelation by using Newey-West standard errors analyze the relationship of media coverage on the ECB in relation to monetary policy. Results of this analysis are shown in Table 1.6.

Table 1.5: The effect of monetary policy conditional on the sophistication of investors

This table shows the results of investor-fixed effects panel regressions on the trading behavior on meeting days of the Governing Board of the ECB for sophisticated and unsophisticated investors. All investors whose average HHI over the whole sample period is below five are considered to be sophisticated (Panel A), the rest is unsophisticated (Panel B). The abnormal trading is measured by excess buy-sell imbalances that relativize trading on meeting days with "normal" trading of the corresponding year. The excess buy-sell imbalances are measured in terms of the number of transactions ("#") and the monetary value ("EUR"). Investigating trading in equity and fixed income securities separately enables to account for different transmission channels of monetary policy. There are three different variables that account for monetary policy decisions of the ECB ("expected change", "conventional surprise" and "unconventional surprise") between 1999 and 2015 differentiating for three periods: "Pre-Crisis" (before the start of the crisis on 22 August 2007), "Crisis" (after 22 August 2007 but before rates hit the zero lower bound on 5 July 2012) and "ZLB" (rates at the zero lower bound starting 5 July 2012). All control variables are included in each regression. p-values based on heteroskedastic-robust standard errors are reported in parentheses. Note: ***, **, * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	All Securities		Equity		Fixed Income	
	#	EUR	#	EUR	#	EUR
			Panel A: Sophisticated			
Normal Market Period (Pre-Crisis)						
Conventional Surprise	0.107***	0.110***	0.0695*	0.0721*	0.185	0.190
	(0.0355)	(0.0366)	(0.0372)	(0.0383)	(0.178)	(0.180)
Expected Change	-0.185***	-0.181***	-0.277***	-0.286***	0.239	0.254
	(0.0451)	(0.0466)	(0.0486)	(0.0502)	(0.198)	(0.206)
Crisis Period						
Conventional Surprise	-0.327***	-0.374***	-0.0649	-0.0585	-0.185	-0.257
	(0.0770)	(0.0800)	(0.0972)	(0.101)	(0.295)	(0.298)
Expected Change	-0.136	-0.193**	0.0110	-0.00434	-0.714**	-0.823**
	(0.0891)	(0.0929)	(0.111)	(0.116)	(0.322)	(0.335)
Unconventional Surprise	0.0279**	0.0332***	0.0744***	0.0835***	0.112***	0.116***
	(0.0114)	(0.0118)	(0.0136)	(0.0140)	(0.0363)	(0.0370)
Zero Lower Bound Period						
Conventional Surprise	0.834**	0.529	-0.606	-0.671	-2.310**	-2.164*
	(0.343)	(0.362)	(0.447)	(0.458)	(1.140)	(1.134)
Expected Change	1.604***	1.187***	0.402	0.226	-1.317	-1.009
	(0.429)	(0.452)	(0.550)	(0.563)	(1.413)	(1.418)
Unconventional Surprise	-0.00187	-0.00278	-0.00290	0.000240	0.0127	0.0120
	(0.00770)	(0.00804)	(0.0100)	(0.0103)	(0.0226)	(0.0234)

(continued)

Panel B: Unsophisticated						
Normal Market Period (Pre-Crisis)						
Conventional Surprise	0.00751	0.0110	0.0194	0.0217	0.307**	0.284*
	(0.0158)	(0.0160)	(0.0169)	(0.0171)	(0.155)	(0.157)
Expected Change	-0.0386*	-0.0301	-0.0476**	-0.0440*	-0.122	-0.104
	(0.0204)	(0.0208)	(0.0223)	(0.0227)	(0.193)	(0.200)
Crisis Period						
Conventional Surprise	-0.0883***	-0.130***	0.131***	0.127***	-0.0650	0.0234
	(0.0334)	(0.0342)	(0.0467)	(0.0476)	(0.260)	(0.263)
Expected Change	-0.0563	-0.0997**	0.130**	0.109**	0.0750	0.138
	(0.0387)	(0.0396)	(0.0529)	(0.0542)	(0.300)	(0.305)
Unconventional Surprise	0.0260***	0.0264***	0.0805***	0.0854***	0.285***	0.300***
	(0.00584)	(0.00601)	(0.00786)	(0.00803)	(0.0307)	(0.0315)
Zero Lower Bound Period						
Conventional Surprise	1.193***	1.103***	0.651**	0.617**	-1.902*	-2.084*
	(0.162)	(0.170)	(0.255)	(0.261)	(1.097)	(1.131)
Expected Change	1.384***	1.254***	1.107***	0.983***	-1.378	-1.648
	(0.205)	(0.214)	(0.321)	(0.327)	(1.371)	(1.406)
Unconventional Surprise	-0.0169***	-0.0182***	-0.0245***	-0.0228***	0.0271	0.0237
	(0.00363)	(0.00373)	(0.00552)	(0.00564)	(0.0237)	(0.0245)
Controls	YES	YES	YES	YES	YES	YES
Year-Fixed Effects	YES	YES	YES	YES	YES	YES
Month-Fixed Effects	YES	YES	YES	YES	YES	YES

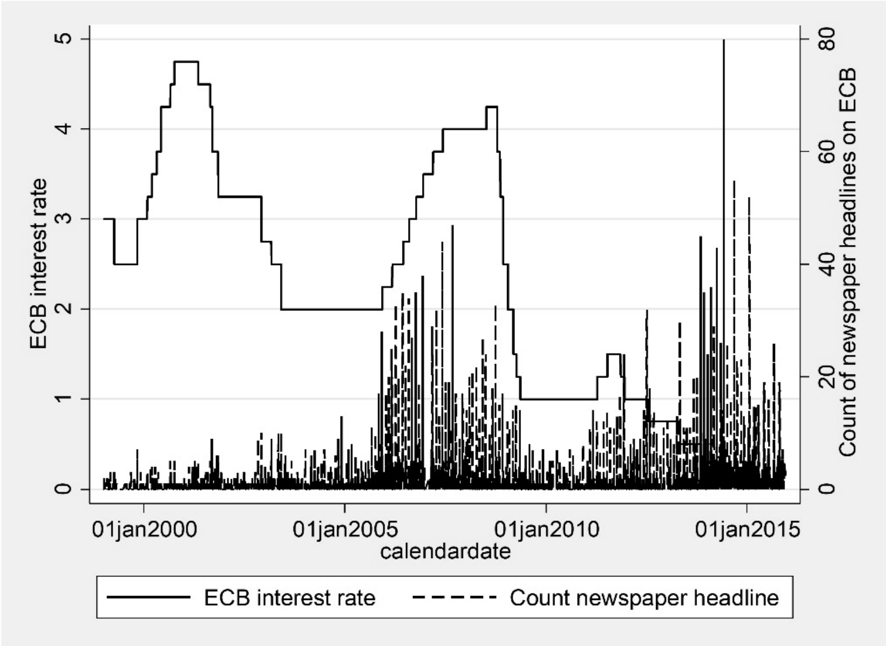

Figure 1.1: ECB actions and newspaper coverage

This figure presents a count of digital German newspaper articles in LexisNexis that contain the word "EZB" (English: ECB) in their headline on a daily base (dashed bars) and the development of the main interest rate of the ECB in percentage points (solid line). The period lasts from 01.01.1999 until 31.12.2015.

Table 1.6: The effect of monetary policy on media coverage

This table shows the results of regressions of the media coverage on the ECB on meeting days of the Governing Council of the ECB. The data on news coverage stem from LexisNexis and count daily headlines, which are about and contain the German word "EZB" (in English "ECB") from 1999 to 2015. Monetary policy variables are dummies that are one if a meeting takes place on the corresponding day and zero otherwise. The periods are split similar to those in the main analysis. Newey West standard errors control for autocorrelation. Note: ***, **, * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	# of headlines in newspaper articles on "ECB"		
	(1)	(2)	(3)
Meeting Full sample	8.853***		
	(0.810)		
Meeting Pre Crisis		0.007	
		(0.147)	
Meeting Crisis		14.174***	
		(1.413)	
Meeting Pre Crisis			0.421***
			(0.111)
Meeting Crisis before ZLB			6.842***
			(0.687)
Meeting ZLB			23.088***
			(3.066)

The first regression for the full sample period in column 1 of Table 1.6 shows that on days with a monetary policy meeting, the amount of articles about the ECB increases by eight compared with normal trading days without a meeting. The second regression in column 2 specifies the impact to be strongly driven by the period of the financial crisis that is defined similarly to previous analyses to begin on 22 August 2007. While the coefficient on newspaper coverage before the start of the crisis is not significantly different from zero, the one within the crisis clarifies the importance. On meeting days during the crisis, there are 14 newspaper articles more than on normal trading days. The third specification differentiates for the three periods used in all analyses and displays the strongest effect on media coverage in the last period. While all coefficients are highly statistically significant, meeting days at the ZLB lead to an increase of the amount of newspaper articles on the ECB of 23. This gives evidence of a reinforcement of the attention effect with the ongoing crisis. This media attention seems to affect predominantly unsophisticated investors, which is commensurate with previous literature by Barber & Odean (2008).

The next sample split focuses on the effect of different levels of wealth on the investment decisions with regard to monetary policy. Table 1.7 shows results for wealthy (Panel A) and less wealthy (Panel B) private investors measured by their average portfolio value.

The first two columns of Panel A show that coefficients for all policy variables are highly statistically significant, thus the wealthy investors are characterized by very strong reactions to policy decisions over all periods. The direction of their abnormal trades does not deviate from that of the whole sample of investors; however, the coefficients are bigger in magnitude. In contrast to the wealthy investors, the less wealthy ones in Panel B have only very few statistically significant coefficients in terms of their trading in all securities. They do not seem to respond to monetary policy, particularly compared to other trading days of the corresponding year.

While the sophisticated investors less often have significant buy-sell imbalances compared to the unsophisticated investors, the split by wealth reveals higher and more significant excess buy-sell imbalances of the wealthy investors. This contradicts evidence of previous studies showing that wealth and financial sophistication often lead to similar results (Dhar & Zhu (2006), Calvet, Campbell & Sodini (2009b)). To investigate these discrepancies in more detail, the subgroups of sophisticated investors are split by their wealth, which results in four additional subsamples.

Table 1.7: The effect of monetary policy conditional on the wealth of investors

This table shows the results of investor-fixed effects panel regressions on the trading behavior on meeting days of the Governing Board of the ECB for wealthy and less wealthy investors. The wealthy investors are those whose average monthly portfolio value over the sample period is above the median in the majority of times (Panel A), the less wealthy ones are those below (Panel B). Abnormal trading is measured by excess buy-sell imbalances that relativize trading on meeting days with "normal" trading of the corresponding year. The excess buy-sell imbalances are measured in terms of the number of transactions ("#") and the monetary value ("EUR"). Investigating trading in equity and fixed income securities separately enables to account for different transmission channels of monetary policy. There are three different variables that account for monetary policy decisions of the ECB ("expected change", "conventional surprise" and "unconventional surprise") between 1999 and 2015 differentiating for three periods: "Pre-Crisis" (before the start of the crisis on 22 August 2007), "Crisis" (after 22 August 2007 but before rates hit the zero lower bound on 5 July 2012) and "ZLB" (rates at the zero lower bound starting 5 July 2012). All control variables are included in each regression. p-values based on heteroskedastic-robust standard errors are reported in parentheses. Note: ***, **, * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	All Securities		Equity		Fixed Income	
	#	EUR	#	EUR	#	EUR
Panel A: Wealthy						
Normal Market Period (Pre-Crisis)						
Conventional Surprise	0.0469**	0.0476**	0.0416**	0.0390*	0.225*	0.196
	(0.0195)	(0.0198)	(0.0203)	(0.0207)	(0.133)	(0.136)
Expected Change	-0.0581**	-0.0469*	-0.0522**	-0.0524*	-0.00307	0.0121
	(0.0246)	(0.0252)	(0.0262)	(0.0269)	(0.157)	(0.165)
Crisis Period						
Conventional Surprise	-0.184***	-0.238***	0.0974*	0.0952*	-0.0765	-0.0704
	(0.0418)	(0.0431)	(0.0527)	(0.0541)	(0.220)	(0.224)
Expected Change	-0.0888*	-0.156***	0.0785	0.0480	-0.231	-0.273
	(0.0481)	(0.0496)	(0.0599)	(0.0619)	(0.247)	(0.255)
Unconventional Surprise	0.0354***	0.0386***	0.0822***	0.0892***	0.207***	0.215***
	(0.00687)	(0.00707)	(0.00841)	(0.00860)	(0.0280)	(0.0285)
Zero Lower Bound Period						
Conventional Surprise	1.489***	1.367***	0.652**	0.580**	-1.887**	-1.715*
	(0.196)	(0.206)	(0.270)	(0.277)	(0.946)	(0.969)
Expected Change	1.967***	1.799***	1.328***	1.147***	-1.047	-0.825
	(0.246)	(0.257)	(0.336)	(0.343)	(1.188)	(1.218)
Unconventional Surprise	-0.0143***	-0.0155***	-0.0191***	-0.0175***	0.0217	0.0199
	(0.00432)	(0.00447)	(0.00580)	(0.00591)	(0.0195)	(0.0201)

(continued)

Panel B: Less wealthy						
<u>Normal Market Period (Pre-Crisis)</u>						
Conventional Surprise	-0.00366	0.00339	0.00479	0.0139	0.365	0.411*
	(0.0217)	(0.0219)	(0.0236)	(0.0238)	(0.243)	(0.241)
Expected Change	-0.0681**	-0.0651**	-0.147***	-0.143***	0.207	0.229
	(0.0285)	(0.0289)	(0.0321)	(0.0325)	(0.306)	(0.309)
<u>Crisis Period</u>						
Conventional Surprise	-0.0506	-0.0770*	0.0938	0.0946	-0.271	-0.175
	(0.0447)	(0.0458)	(0.0703)	(0.0718)	(0.423)	(0.422)
Expected Change	-0.0403	-0.0564	0.149*	0.151*	-0.429	-0.296
	(0.0524)	(0.0536)	(0.0793)	(0.0808)	(0.482)	(0.483)
Unconventional Surprise	0.0155*	0.0142*	0.0777***	0.0816***	0.228***	0.244***
	(0.00794)	(0.00818)	(0.0116)	(0.0119)	(0.0444)	(0.0459)
<u>Zero Lower Bound Period</u>						
Conventional Surprise	0.569***	0.428*	-0.244	-0.215	-2.670*	-3.256**
	(0.219)	(0.229)	(0.392)	(0.399)	(1.436)	(1.413)
Expected Change	0.614**	0.405	0.159	0.120	-2.177	-2.816
	(0.279)	(0.290)	(0.495)	(0.505)	(1.743)	(1.719)
Unconventional Surprise	-0.0132***	-0.0145***	-0.0193**	-0.0160*	0.0167	0.0132
	(0.00503)	(0.00518)	(0.00877)	(0.00900)	(0.0309)	(0.0318)
Controls	YES	YES	YES	YES	YES	YES
Year-Fixed Effects	YES	YES	YES	YES	YES	YES
Month-Fixed Effects	YES	YES	YES	YES	YES	YES

Table 1.8 displays excess buy-sell imbalances of sophisticated investors and divides them into wealthy and less wealthy subject to the median portfolio value of the sophisticated investors. Panel A, which shows the wealthy sophisticated investors, reveals coefficients that are very similar to those of the whole group of sophisticated investors.

Most effects are in line with those for the entire group of sophisticated investors; however, the wealthy sophisticated investors hardly react to unconventional policy announcements in terms of trading in securities in general. Yet, during the crisis before the ZLB, the split for equity and fixed income reveals significant sales of both types if the announcement is more expansive than expected. A possible reason for this observation is a rebalancing to other asset classes like commodities such as gold.

Looking at the sophisticated but less wealthy investors in Panel B of Table 1.8, the directions of their trading patterns are similar to those of Panel A. However, there is no effect during the period at the ZLB.

Thus, the main difference between more and less wealthy investors with the same rather high level of sophistication is the absence of significant reactions of the latter when interest rates are close to the ZLB.

Table 1.9 displays abnormal trading of the unsophisticated investors split by their median monthly portfolio value. Panel A, which contains the rather wealthy unsophisticated investors, does not give evidence for any effects of excess buying or selling subject to monetary policy before the start of the crisis in 2007. Neither the whole sample of all securities nor the subsets of single asset classes show any effect. This suggests that this group of investors does not pay close attention to the monetary policy of the ECB in normal market times. In contrast, after the start of the crisis, they show significant reactions to conventional decisions that have the expected sign of buying securities whenever monetary policy is more expansive. These coefficients reverse for unconventional policy and the entire ZLB period. There, loosening policy decisions are perceived as a negative signal since the coefficients are positive and highly statistically significant, which can be interpreted as investors selling securities. Particularly, the right columns show that this group of investors loses interest in equity positions. With interest rates close to zero, unconventional monetary loosening starts to become effective in its intended way. The negative signs indicate purchases, predominantly of equity positions, with respect to expansive policy.

Table 1.8: The effect of monetary policy on sophisticated investors conditional on their wealth

This table shows the results of investor-fixed effects panel regressions on the trading behavior on meeting days of the Governing Board of the ECB for the sophisticated investors split for their wealth. The investors are defined to be sophisticated if their average HHI over the whole sample period is below five. This group is then further divided subject to its wealth where the wealthy investors are those whose average wealth over the sample period is above the median (Panel A), the less wealthy ones are those whose wealth is below (Panel B). Abnormal trading is measured by excess buy-sell imbalances that relativize trading on meeting days with "normal" trading of the corresponding year. The excess buy-sell imbalances are measured in terms of the number of transactions ("#") and the monetary value ("EUR"). Investigating trading in equity and fixed income securities separately enables to account for different transmission channels of monetary policy. There are three different variables that account for monetary policy decisions of the ECB ("expected change", "conventional surprise" and "unconventional surprise") between 1999 and 2015 differentiating for three periods: "Pre-Crisis" (before the start of the crisis on 22 August 2007), "Crisis" (after 22 August 2007 but before rates hit the zero lower bound on 5 July 2012) and "ZLB" (rates at the zero lower bound starting 5 July 2012). All control variables are included in each regression. p-values based on heteroskedastic-robust standard errors are reported in parentheses. Note: ***, **, * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	All Securities		Equity		Fixed Income	
	#	EUR	#	EUR	#	EUR
			Panel A: Wealthy			
Normal Market Period (Pre-Crisis)						
Conventional Surprise	0.0963**	0.0956**	0.0585	0.0596	0.210	0.204
	(0.0404)	(0.0417)	(0.0422)	(0.0435)	(0.193)	(0.195)
Expected Change	-0.186***	-0.182***	-0.262***	-0.268***	0.320	0.358
	(0.0512)	(0.0531)	(0.0551)	(0.0571)	(0.213)	(0.221)
Crisis Period						
Conventional Surprise	-0.303***	-0.359***	0.0146	0.0250	-0.134	-0.189
	(0.0891)	(0.0925)	(0.112)	(0.116)	(0.320)	(0.325)
Expected Change	-0.143	-0.219**	0.0234	-0.00497	-0.730**	-0.886**
	(0.103)	(0.107)	(0.129)	(0.134)	(0.351)	(0.368)
Unconventional Surprise	0.0200	0.0267*	0.0718***	0.0830***	0.135***	0.138***
	(0.0136)	(0.0141)	(0.0162)	(0.0167)	(0.0418)	(0.0422)
Zero Lower Bound Period						
Conventional Surprise	0.942**	0.621	-0.540	-0.605	-2.595*	-2.420*
	(0.403)	(0.420)	(0.520)	(0.531)	(1.338)	(1.332)
Expected Change	1.713***	1.261**	0.484	0.327	-1.293	-0.958
	(0.500)	(0.520)	(0.635)	(0.645)	(1.673)	(1.678)
Unconventional Surprise	-0.00231	-0.00329	-0.00789	-0.00374	0.0313	0.0321
	(0.00892)	(0.00927)	(0.0116)	(0.0118)	(0.0264)	(0.0269)

(continued)

	Panel B: Less Wealthy					
Normal Market Period (Pre-Crisis)						
Conventional Surprise	0.140*	0.155**	0.106	0.113	0.0275	0.0799
	(0.0742)	(0.0760)	(0.0793)	(0.0812)	(0.451)	(0.453)
Expected Change	-0.182*	-0.180*	-0.331***	-0.346***	-0.193	-0.293
	(0.0950)	(0.0979)	(0.103)	(0.106)	(0.519)	(0.540)
Crisis Period						
Conventional Surprise	-0.417***	-0.434***	-0.368*	-0.376*	-0.393	-0.555
	(0.152)	(0.157)	(0.195)	(0.204)	(0.746)	(0.722)
Expected Change	-0.125	-0.112	-0.0605	-0.0330	-0.607	-0.492
	(0.177)	(0.184)	(0.216)	(0.226)	(0.803)	(0.805)
Unconventional Surprise	0.0462**	0.0478**	0.0765***	0.0806***	0.0294	0.0386
	(0.0209)	(0.0213)	(0.0250)	(0.0257)	(0.0721)	(0.0763)
Zero Lower Bound Period						
Conventional Surprise	0.529	0.254	-0.802	-0.844	-1.381	-1.391
	(0.656)	(0.718)	(0.869)	(0.901)	(2.032)	(1.966)
Expected Change	1.286	0.957	0.136	-0.0740	-1.060	-0.962
	(0.837)	(0.913)	(1.104)	(1.148)	(2.411)	(2.397)
Unconventional Surprise	-0.000366	-0.00102	0.0127	0.0128	-0.0454	-0.0523
	(0.0152)	(0.0162)	(0.0199)	(0.0207)	(0.0425)	(0.0463)
Controls	YES	YES	YES	YES	YES	YES
Year-Fixed Effects	YES	YES	YES	YES	YES	YES
Month-Fixed Effects	YES	YES	YES	YES	YES	YES

Table 1.9: The effect of monetary policy on unsophisticated investors conditional on their wealth

This table shows the results of investor-fixed effects panel regressions on the trading behavior on meeting days of the Governing Board of the ECB for the unsophisticated investors split for their wealth. The investors are defined to be unsophisticated if their average HHI over the whole sample period is above four. This group is then further divided subject to its wealth where the wealthy investors are those whose average wealth over the sample period is above the median (Panel A), the less wealthy ones are those whose wealth is below (Panel B). Abnormal trading is measured by excess buy-sell imbalances that relativize trading on meeting days with "normal" trading of the corresponding year. The excess buy-sell imbalances are measured in terms of the number of transactions ("#") and the monetary value ("EUR"). Investigating trading in equity and fixed income securities separately enables to account for different transmission channels of monetary policy. There are three different variables that account for monetary policy decisions of the ECB ("expected change", "conventional surprise" and "unconventional surprise") between 1999 and 2015 differentiating for three periods: "Pre-Crisis" (before the start of the crisis on 22 August 2007), "Crisis" (after 22 August 2007 but before rates hit the zero lower bound on 5 July 2012) and "ZLB" (rates at the zero lower bound starting 5 July 2012). All control variables are included in each regression. p-values based on heteroskedastic-robust standard errors are reported in parentheses. Note: ***, **, * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	All Securities		Equity		Fixed Income	
	#	EUR	#	EUR	#	EUR
Panel A: Wealthy						
Normal Market Period (Pre-Crisis)						
Conventional Surprise	0.0318	0.0331	0.0364	0.0329	0.224	0.176
	(0.0222)	(0.0225)	(0.0232)	(0.0235)	(0.181)	(0.186)
Expected Change	-0.0181	-0.00463	0.0112	0.0131	-0.310	-0.316
	(0.0280)	(0.0287)	(0.0297)	(0.0304)	(0.218)	(0.231)
Crisis Period						
Conventional Surprise	-0.148***	-0.202***	0.122**	0.116*	-0.00517	0.0510
	(0.0474)	(0.0486)	(0.0597)	(0.0610)	(0.300)	(0.306)
Expected Change	-0.0755	-0.139**	0.0914	0.0603	0.219	0.265
	(0.0544)	(0.0558)	(0.0677)	(0.0696)	(0.341)	(0.350)
Unconventional Surprise	0.0400***	0.0421***	0.0846***	0.0902***	0.264***	0.277***
	(0.00796)	(0.00817)	(0.00983)	(0.0100)	(0.0370)	(0.0381)
Zero Lower Bound Period						
Conventional Surprise	1.657***	1.598***	1.047***	0.973***	-1.195	-1.013
	(0.224)	(0.236)	(0.315)	(0.323)	(1.342)	(1.405)
Expected Change	2.034***	1.958***	1.594***	1.409***	-0.739	-0.592
	(0.282)	(0.296)	(0.394)	(0.402)	(1.689)	(1.765)
Unconventional Surprise	-0.0182***	-0.0194***	-0.0232***	-0.0226***	0.0134	0.00949
	(0.00495)	(0.00510)	(0.00670)	(0.00683)	(0.0283)	(0.0296)

(continued)

	Panel B: Less Wealthy					
Normal Market Period (Pre-Crisis)						
Conventional Surprise	-0.0176	-0.0110	-0.00264	0.00651	0.483*	0.515*
	(0.0227)	(0.0229)	(0.0247)	(0.0249)	(0.285)	(0.283)
Expected Change	-0.0587**	-0.0555*	-0.125***	-0.119***	0.348	0.428
	(0.0299)	(0.0303)	(0.0338)	(0.0342)	(0.380)	(0.378)
Crisis Period						
Conventional Surprise	-0.0174	-0.0450	0.148**	0.149*	-0.147	0.0850
	(0.0468)	(0.0479)	(0.0754)	(0.0767)	(0.511)	(0.514)
Expected Change	-0.0320	-0.0512	0.180**	0.178**	-0.259	-0.104
	(0.0549)	(0.0561)	(0.0852)	(0.0866)	(0.599)	(0.598)
Unconventional Surprise	0.00894	0.00706	0.0746***	0.0783***	0.335***	0.355***
	(0.00858)	(0.00885)	(0.0131)	(0.0134)	(0.0545)	(0.0554)
Zero Lower Bound Period						
Conventional Surprise	0.582**	0.458*	-0.114	-0.0679	-3.578*	-4.470**
	(0.232)	(0.241)	(0.437)	(0.444)	(1.898)	(1.864)
Expected Change	0.516*	0.323	0.138	0.141	-2.815	-3.888*
	(0.296)	(0.305)	(0.553)	(0.561)	(2.341)	(2.287)
Unconventional Surprise	-0.0151***	-0.0165***	-0.0264***	-0.0224**	0.0629	0.0610
	(0.00533)	(0.00545)	(0.00976)	(0.00999)	(0.0432)	(0.0429)
Controls	YES	YES	YES	YES	YES	YES
Year-Fixed Effects	YES	YES	YES	YES	YES	YES
Month-Fixed Effects	YES	YES	YES	YES	YES	YES

The second part of Table 1.9 displays excess buy-sell imbalances of the less wealthy unsophisticated investors (Panel B). Similar to the results for the sophisticated and less wealthy investors (Table 1.8, Panel B), the unsophisticated ones below the median portfolio value show considerably fewer reactions in terms of their abnormal trades compared with the more wealthy ones. In the first period before the start of the crisis, the coefficients on trading in all securities are negative but only slightly significant for expected changes so as to these investors align their trading decisions with capital market reactions. The direction of their trades reverses during the ZLB period, where this group of investors rather sells securities subject to conventional rate decreases. However, except for the unconventional surprises at the ZLB, none of the coefficients shows significance levels below 5%.

1.5 Conclusion of Chapter 1

Actively trading German retail investors in general take account of monetary policy actions of the ECB during the whole sample period. They significantly alter their trading behavior but the direction of these trades depends on the period. For conventional decisions between 1999 and the beginning of the financial crisis in 2007, the inverse relation also found for capital markets holds. Obviously, private investors react to monetary policy quite rationally in all market times as long as they are used to the way of signaling.

In contrast, unconventional announcements during the crisis and conventional announcements near the ZLB reveal a change in reactions. The investors no longer enter the market on expansive signals but rather exit. This way, investors might interpret these latter announcements as signals of a weak economic situation. A period of rates at the ZLB is completely new to European markets and investors, which might be the reason why the normal signaling channels do not work the way they used to. The same rationale is applicable to unconventional monetary policy, which has never been implemented before in the euro area. With rates at the ZLB, the announcement of unconventional policy affects the investors in the intended direction after all. This rather indicates that investors have faith in the ECB in stabilizing financial markets, than an understanding of the expansive nature of these interventions.

For trading in all securities, the difference between the wealthy and less wealthy investors is considerably strong. The less wealthy investors trade less than the overall investors in the sample. Therefore, the more wealthy investors cause most of the trading observed in the whole sample. This tendency to trade heavily has already been shown in the context of private investor trading where Carroll (2002) gives evidence for an inverse relation between an investor's wealth and risk aversion and Calvet, Campbell, & Sodini (2007) show that higher wealth leads to transactions that are more aggressive. In contrast, subject to the fact that investors with a higher portfolio value are exposed to market reactions more strongly, they might also be more interested in the processes on these markets.

The split by sophistication reveals differing reactions in different periods. The sophisticated investors in this sample predominantly buy securities on expansive signals of the ECB before interest rates approach the ZLB. In contrast, the unsophisticated investors exit the capital market on the same signals after the start of the financial crisis. This observation might partly be subject to a higher news coverage after the start of the crisis, which is also supported by an increase of investor attention during recessions (Andrei & Hasler (2015)) or an increase of risk aversion (Guiso, Sapienza & Zingales (2013)).

The split for asset classes reveals that equity and fixed income securities seem to be substitutes whereby the demand for either of them depends on the specification of a monetary policy decision and the subperiod. During the financial crisis and for conventional decisions at the ZLB, expansive signals result in a shift from equity to fixed income positions. This might be evidence for a higher trust in the latter, which would be in line with a flight to safety of the whole investor sample. This is also evident in the research on market reactions to monetary policy decisions of the BoE by Florackis, Kontonikas, & Kostakis (2014).

The unsophisticated investors, who sell equity on expansive monetary policy signals during the crisis and for conventional decisions at the ZLB, seem to be afraid and therefore reduce their equity positions. In contrast, the more sophisticated investors, who keep their positions constant for most monetary policy variables, are affected to a lesser degree.

In conclusion, monetary policy actions of the ECB seem to affect the asset allocation of investors in Germany to a significant amount. Finding considerable differences between the different subgroups of investors in principle gives initial evidence for potential redistributional effects caused by monetary policy decisions.

Chapter 2: Dissecting private investor performance and trading motives in innovative financial products

2.1 Introduction to Chapter 2

Financial innovations aim to provide an improved product that can better satisfy investors' demands (Frame & White (2004)). Since the beginning of the 2000s, one of the most recent product innovations of retail markets has been structured financial products (SFPs). These products offer predefined payout functions that depend on the performance of an underlying financial asset without requiring the investor to actually purchase the underlying product.[8] Thus, these products enable private investors to protect their initial investments or to use a leverage factor to disproportionally participate in the performance of the underlying.

In assessing the impact of SFPs, international research has focused on the product level, pricing structure and issuer benefits of these products. In terms of pricing, Müller et al. (2017) provide evidence on the pricing structure of investment structured financial products (ISFPs), and Entrop, Schober, & Wilkens (2011) and Vokatá (2018) show that banks issuing SFPs benefit from the complex pricing structure at the expense of the private investors who purchase these products. Additionally, Egan (2018) finds that brokers advise suboptimal products that offer a higher provision to themselves but lower coupons to investors. For small samples and a limited set of different types of SFPs – e.g., discount and bonus certificates, which belong to ISFPs – Entrop et al. (2016) provide evidence on an underperformance towards the DAX underlying. In contrast, using a very similar dataset in terms of time period, product type and origin, other studies, such as the study by Nicolaus (2010), find the opposite results. For a 10-month period and for knock out products only, Meyer, Schroff & Weinhardt (2014) find that the type of underlying, either an index or a single stock, determines the return. Thus, previous studies focusing on the performance of SFPs paint an ambiguous picture.

However, the performance of investors using such products may be different from the performance of all products in the markets or in the entire period, as trading in those products may depend on factors, such as sentiment, economic expectations and many considerations that are more individual. Only the papers by Calvet et al. (2016 and 2017) focus on the usage of those products in household portfolios. These papers show a positive relation between newly participating in the stock market and investing in SFPs for risk averse investors.

[8] Underlyings are other financial assets, such as stocks, bonds, funds, commodities, currencies or any other product.

Extending the previous research, our study focuses on the following questions with regards to trading leveraged structured financial products (LSFPs). Who buys LSFPs? How does the performance in LSFPs compare to the performance in other asset classes? With what intention do investors buy these products: do they aim to hedge existing positions, or do they try to factor their performance? Do specific investor and trading characteristics or motives affect the performance?

In trying to answer these questions, we use a representative dataset of self-directed German retail investors of a large German online broker. The dataset contains transactional data from 60,986 investors with an average portfolio value of 47,035 euros and, on average, 474 trades, particularly in single stocks, funds and SFPs between 2000 and 2015. Characteristics, such as the portfolio value or investor age, indicate that this dataset is representative of German investors and highly comparable to the data in the international research on private investor trading.

Based on our data, we estimate that there are 1.16 million German investors in SFPs. This number is equivalent to 4.4% of all German security accounts. Of these investors, 78% trade ISFPs and 65% trade LSFPs. Over the sample period, the number of users reaches its maximum of approximately 25,000 SFP users in 2008, and then, this number decreases to 18,000 in 2015. These investors use both ISFPs and LSFPs, and these positions account for more than 20% of their portfolio value. This suggests that, among German retail investors, SFPs are an important investment product.

In a first step, we test whether users of LSFPs differ from investors not trading these securities. Thus, we compare the characteristics incorporated in our data between these groups of investors. We find that LSFP users have a higher portfolio value, classify themselves as less risk averse and generally trade more not only in SFPs but also in other financial products, particularly in single stocks. LSFP users take into account their own past investment outcomes when making investment decisions in LSFPs. Negative experiences seem to be the main driver of these decisions, as LSFP users increase their turnover in LSFPs after bad past returns.

Second, in assessing the performance of investors in LSFPs from the trade-based perspective, we compute round trip returns as the difference between the purchase and sale prices for every trade executed by the investors in our sample. This return is positive before (1.54%) and negative after (-0.70%) transaction costs. These trades have a large heterogeneity. This fact is reflected by a positive median gross return of 2.61% (net 1.25%), which is quite large when relating this number to the median round trip length of only two days. This suggests that more than half of these trades yield a large and positive return. The average returns in stocks and ISFPs are smaller in terms of both gross and net returns. Compared with a direct investment in the corresponding underlying, LSFPs offer higher returns.

As round trips focus exclusively on completed transactions, they ignore positions that are not properly closed but are either knocked out (as may be the case for LSFPs) or not sold yet. These positions negatively affect the return of stocks, ISFPs and LSFPs. Combining the gross returns of the complete and incomplete transactions of these products, on average, investors lose 0.79% per trade in LSFPs and 1.28% from stocks. By testing the robustness of our results by investigating counterfactual portfolios that exclude LSFPs, we confirm the previous evidence. Analyses that aim to identify the potential drivers of this negative portfolio contribution suggest that the underperformance is based on the trading decisions of private investors. Thereby, inexperience and overtrading seem to be the most promising sources of explanation.

Sample splits for the trading motives of LSFP users show large differences between the user groups. Before transaction costs, investments that target the accumulation of capital (either from dynamic hedgers or speculators) generate positive returns. In contrast, investors who aim to protect already existing portfolio positions using LSFPs face large losses. Consequently, the intention of a trade rather than the product itself seems to determine the outcome of an investment.

With our findings, we add to the literature in several ways. First, we confirm some of the investment mistakes found in retail investor trading in general for other asset classes. Odean (1999) and Barber & Odean (2000), who investigate trading in stocks, show that trading too much lowers the returns on investments. Exchange traded funds (ETFs), a financial innovation in the fund market, closely track a broadly diversified index at very low costs. Bhattacharya et al. (2016) show that the investment mistakes established in stock trading also occur for ETFs and lead to suboptimal returns. This situation, however, is not a problem caused by the product structure itself but results from the investment behavior of individuals. The excessive trading of the investors leads to the high transaction costs that negatively affect the performance.

Our results are in line with the results obtained by these previous authors when examining investors who trade in LSFPs. The counterfactual analysis shows that excessive trading is one of the determinants of performance losses. While on average, completed round trip returns in LSFPs are positive, after transaction costs, investors lose money. This phenomenon is evident especially for speculators, who have the highest turnover.

Second, we add to the literature on SFPs, which, so far, has focused on the pricing of these products and on making a general performance assessment of them, while ignoring the behavior of single investors. Instead of generally finding negative outcomes from investing in LSFPs (Entrop et al. (2016), Nicolaus (2010)), we show that the trading motive is an important determinant of returns.

Third, Blonski & Blonski (2016) theoretically explain that, in general, complex financial products are detrimental to investors' investment outcomes, as investors cannot optimally decide how to invest in products they do not completely understand. Following Célérier & Vallée (2017), we measure product complexity by counting the number of scenarios in the payout function. The complexity of LSFPs in our sample ranges from 1 to 4 payout scenarios. In contrast to previous findings, the worst performance seems to come from the rather simple products that have only 1 scenario. (These are factor certificates offering a multiple of the performance of the underlying.)

The paper is structured as follows: Section 2.2 broadly describes the product characteristics SFPs offer. In Section 2.3, we describe the datasets on retail investors and on SFPs and their respective underlyings. Section 2.4 contains the main analyses investigating the performance of our sample investors by computing round trip returns and running counterfactual regressions in the portfolio context. In Section 2.5, we investigate the trading motives for LSFP investments. We conclude in Section 2.6.

2.2 The rationale of structured financial products

Regulation prohibits private investors from entering short positions in financial assets. Thus, for long periods, in the case of expectations of negative returns for a specific asset, retail investors could hardly express a negative expectation beyond completely selling a stock. In addition, directly trading in options was and is hardly possible for retail investors. This situation changed during the 1990s when the first SFPs were introduced in Germany, which not only enabled investors to profit from negative market movements but also offered premiums for sideways trends.

The general idea of SFPs is the participation in the performance of financial products – either stocks, bonds, funds, indices, commodities, exchange rates or any other products – which cannot be realized by going long in the financial product itself. Thus, the underlying of the SFP is the product for which the investor has specific expectations, and, to trade on these expectations, she uses an SFP. For instance, if an investor expects a stock she does not own to decrease in the near future, she can trade on this expectation only if she chooses a structured product that offers positive returns when the price of the underlying decreases.

The exact product design differs between the varieties of SFPs that have emerged over the past 20 years. Figure 2.1 gives an overview of product categories. In general, SFPs can be divided into ISFPs and LSFPs. The former aim at capital protection, yield enhancement or participation in the performance of the underlying, and the latter have a leverage effect that can lead, on the one hand, to a multiple return of the underlying and, on the other hand, to a total loss. These different goals and payout designs result from a variety of product types.

ISFPs with capital protection offer the chance to participate in the upside performance of an underlying and to pay a minimum redemption equal to the capital protection in case the price of the underlying is below the predefined value at maturity. In this way, ISFPs assure a certain minimum repayment to investors. Yield enhancement products pay a predefined amount of capital if the underlying touches or hits the strike price; otherwise, the underlying is redeemed, or the payout reflects 1:1 the price of the underlying. Thus, in the case of a positive performance of the underlying, the return increases by additional payments, while a negative performance will be completely realized. In contrast, participation products do not exhibit a payout cap but unlimitedly (proportionally or disproportionally) participate in the upside performance of the underlying.[9]

[9] For both ISFPs and LSFPs, the loss is limited to the initial investment.

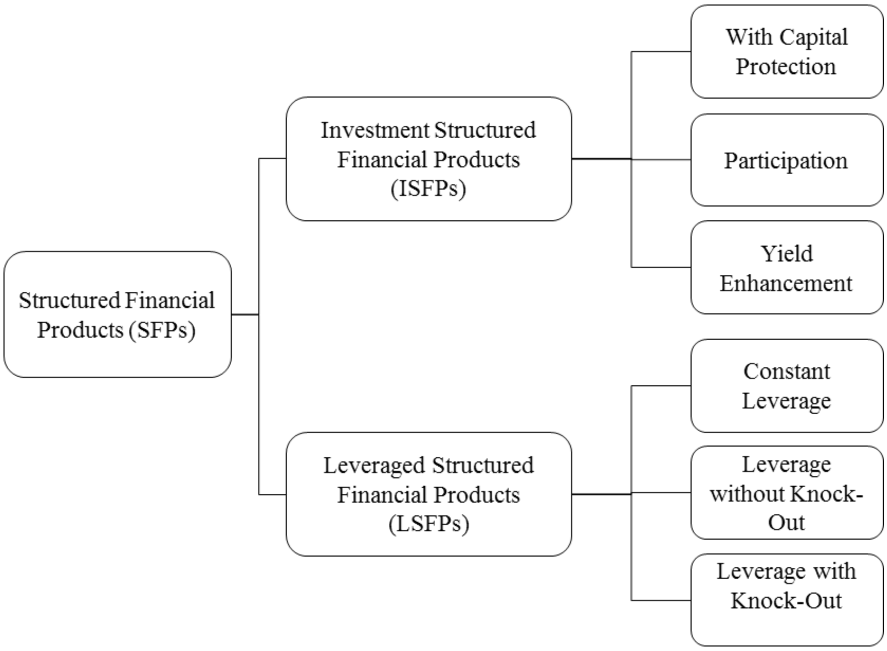

Figure 2.1: The classification of SFPs

LSFPs are characterized by small capital investments, which offer the chance of high profits subject to the leveraged performance. LSFPs come with or without knock out. Products with knock out face the risk of expiring as worthless as soon as the price of the underlying hits a price barrier during the product lifetime. For the products without knock out, the actual price determines the amount of loss. Subject to the actual price, there is either a partial repayment or a total loss. In terms of positive payouts, however, classical warrants have no upper barrier restricting gains. With a constant leverage or factor certificate, an investor disproportionally participates in the price development of the underlying. The factor can be quite large, with a number of up to 30, so positive returns have no limit.[10]

LSFPs account for more than half of the overall turnover in SFPs (Deutscher Derivate Verband (2018a)). At the same time, the share of open interest in LSFPs was only 3% of the total open interest in SFPs of 65 billion euros at the end of October 2018 (Deutscher Derivate Verband (2018b)). Thus, in terms of monetary value, SFPs are strongly dominated by ISFPs.

[10] For a more detailed description of SFPs available, see the derivative map of EUSIPA (https://eusipa.org/wp-content/uploads/European_map_20160530_2016.pdf), which summarizes the products offered.

2.3 Data and research design

For our analysis, we combine three datasets. First, our data consist of information on the type and nature of the SFPs of more than 15 million single products between 1999 and 2015. The data include the name of the underlying, the issuing date, whether it is a put or a call option, and information about the SFP category to which the security belongs. Second, a dataset containing the ISINs of the respective underlyings of the SFPs is added. Third, the sample of German retail investors includes the personal and the trade characteristics of more than 100,000 individuals between 1999 and 2015.

2.3.1 Investors in our sample

The investor data we use come from a large German direct brokerage and include transactional and demographic information – e.g., age, gender, risk attitude and portfolio value – for approximately 100,000 investors who held a customer account within the period ranging from 1999 to the end of 2015 and who traded at least once every year during this period. To ensure that we investigate only the trading of the investors who initiate these transactions, we exclude the investors who use financial advice and transactions that stem from automated trading, such as savings-plans or limit orders. In this way, we end up with only those transactions based on a particular decision of an individual investor and a sample size of 60,986 investors. This final sample of retail customers trades all types of products, including investment and leveraged structured financial products.

Table 2.1 shows the descriptive statistics for the whole sample of investors in our final sample. The average investor is 53 years old and has a portfolio value of 47,035 euros. Of our sample, 84% are male, and 16% are female. With an average risk class of 3.54 and a median risk class of 4 out of 5, these investors trade rather risky securities. This situation is also reflected in the lower panel, which focuses on the investors' trading activities in the asset classes depicted. On average, investors make 474 trades during the sample period. Subdividing these trades into asset classes yields 214 trades in single stocks, 93 trades in funds and 162 trades in SFPs, and the remainder are trades in other financial products. In terms of the usage of asset classes, single stocks are the most popular product, which are traded by 92% of the investors. In addition, 83% use funds, and 56% use SFPs at least once. On average, the private investors in our sample start to trade SFPs in June 2005, while the median investor begins some days earlier. The private investors seem to start investing in LSFPs more than one year earlier than they do in ISFPs.

To assess the representativeness of our dataset, we compare it with official statistics and other scientific datasets on private investors. Deutsche Bundesbank reports official statistics on the German stock market and indicates that its investors' average portfolio values are 48,000 euros (Deutsche Bundesbank (2013)). This number is highly comparable to the one we find in our data, which shows that the investors in our sample are representative of the average German investor. Furthermore, with a portfolio value of this magnitude, we are confident these accounts are not play-money accounts. Using data from an online brokerage may reflect the behavior of self-directed stock market participants fairly well, while it may not be as representative of customers at brick-and-mortar banks, who are known to rely on financial advice and where the advisory processes usually favor mutual funds over direct stock investments or SFPs.

Table 2.1: Descriptive statistics of all investors

This table contains descriptive statistics of the sample investors in three dimensions: personal characteristics, trading characteristics and information on the share of asset classes used by all investors.

		All Investors		
		Observations	Mean	Median
Personal & Portfolio Characteristics	**Unit**			
Gender (Female =1)	percent	60,986	0.16	0.00
Risk Class (1 = most risk averse, max = 5)	category	60,986	3.54	4.00
HHI (1 = not diversified)	percent	60,986	0.22	0.15
Self-employed	percent	60,986	0.20	0.00
Age	years	60,986	52.82	52.00
Portfolio Value	Euros	60,986	47,035	28,235
Academic Title	percent	60,986	0.07	0.00
Married	percent	60,986	0.59	1.00
Trading Characteristics				
Number of Total Trades	count	60,986	474.26	195.00
Number of Trades in single Stocks	count	60,986	214.35	60.00
Number of Trades in Funds	count	60,986	93.19	19.00
Number of Trades in SFPs	count	60,986	161.55	2.00
Value of Trades in SFPs	Euros	60,986	1,023,759	4,039
Average Date of first trading SFPs	Date	33,945	15.06.2005	06.06.2005
Average Date of first trading ISFPs	Date	26,626	06.07.2006	07.04.2006
Average Date of first trading LSFPs	Date	22,077	22.01.2005	21.05.2004
Usage of Asset Classes				
Usage of single Stocks (1 = one trade in stocks)	percent	60,986	0.92	1.00
Usage of Funds (1 = one trade in funds)	percent	60,986	0.83	1.00
Usage of SFPs (1 = one trade in SFP)	percent	60,986	0.56	1.00
Usage of ISFPs (1 = one trade in ISFP)	percent	60,986	0.44	0.00
Usage of LSFPs (1 = one trade in LSFP)	percent	60,986	0.36	0.00

To investigate whether our data are specific to Germany, we further compare our trading data to other empirical, international studies on private investor trading. While the average age is 53 years in our sample, Barber & Odean (2001) and Calvet, Campbell and Sodini (2007) describe an average age of 50 years (US data) and 51 years (Swedish data), respectively. The males in our sample account for 84% of our total sample, which is comparable to the 79% in the sample of Barber and Odean (2001). The average portfolio value of 47,000 euros in our sample is between the values of the samples of Barber and Odean (2001) and Calvet, Campbell and Sodini (2007) with 57,000 euros and 35,000 euros, respectively.

These results show that the dataset can be assumed to be representative for retail investors trading via German direct brokerage firms and are highly comparable to data in other economic research.

2.3.2 Structured financial products and underlyings

In addition to the issuer and the product perspective, it is important to assess the market for SFPs in Germany to obtain an understanding of the number of investors trading in these products. As our data are assumed to be representative, we can estimate the total market size and show these products to be relevant to German retail investors.[11,12]

Comparing the number of trades in the different financial products by all investors in the sample reveals that the percentage of trades in LSFPs (41%) accounts for the highest share among all completed transactions. The magnitude is similar to that for trades in single stocks (38%) and much larger than the number of trades in funds (17%) or in ISFPs (2%). When we relativize these numbers with the average value per trade, single stocks remain the most important product, with a total value of trades of 23 billion euros, followed by LSFPs, which have trades of 14 billion euros. Thus, trades in LSFPs are neither rare nor small. This statement refers to self-directed investors. The number of LSFP users at branch banks is however very small.

To obtain an understanding of the importance of SFP product categories in our data, Table 2.2 shows their share in the market ranked by the number of products (ISINs) available to investors

[11] In Germany, there are approximately 26 million security accounts over every type of brokerage (Deutsche Bundesbank (2017)). Direct brokerages have a market share of 8% (Investors Marketing (2013)). Combining this value with the number of security accounts yields approximately 2 million accounts held at direct brokerages in Germany. As our sample shows, 56% of all investors use SFPs (33,945 of 60,986). This calculation results in 1.16 million German investors in SFPs. The usage of LSFPs amounts to 36% of all investors (22,077 of 60,986). Relating these numbers to 26 million security accounts, roughly 3% or 750,000 of them contain LSFPs.

[12] Comparing the market volume in SFPs to the one in ETFs gives an idea of the importance of the former. In September of 2019, the total German market volume in SFPs amounts to 73.4 billion euros, whereas German private investors hold 26.7 billion euros in ETFs (extraETF (2019), Deutscher Derivate Verband (2019)).

(column 1), the number of product purchases per ISIN (column 2) and the number of products purchased in our sample (column 3). Comparing the share of ISFPs and LSFPs shows that the latter account for more than three quarters of the products available to investors in our sample. The other two columns displaying the investor side show an even stronger tendency for LSFPs compared with ISFPs. In these columns, 90% of the trades on the ISIN level are in LSFPs, and, when adding the total number of trades per SFP category, 93% are in LSFPs. These numbers are even higher than those from the official statistics of the Deutsche Derivate Verband, which demonstrated a share of 60% for trades in LSFPs at the end of 2015 (Deutscher Derivate Verband (2015)).

Table 2.2: Share of SFP categories available to and traded by investors

This table divides SFPs into product groups following the classification of the Deutsche Derivate Verband. For each product group, the share on the market level, on the trading level (both in terms of the product ISIN) and the share of investor trades in our sample are depicted. For some products, no information is available on the product groups other than whether they belong to ISFPs or LSFPs. These products belong to the category "other".

	Market Share (ISIN)	Trading Share (ISIN)	Sample Share (# trades)
ISFP			
With Capital Protection	0.08%	0.08%	0.07%
Participation	3.66%	1.56%	3.33%
Yield Enhancement	20.10%	6.71%	1.70%
Other	2.81%	1.16%	1.75%
Total	26.65%	9.51%	6.84%
LSFP			
Constant Leverage	0.03%	0.19%	1.23%
Leverage without Knock-Out	31.64%	36.72%	45.94%
Leverage with Knock-Out	41.57%	53.23%	45.22%
Other	0.10%	0.35%	0.77%
Total	73.35%	90.49%	93.16%

The most important categories in terms of trading SFPs for all three specifications are leverage products with and without knockout. Even though the exact share of SFPs differs between the market and the investor view, the number of products in this category is by far the largest. Yield enhancement products, which reflect 20% of the products available in the market, amount to only 2% of the actual product purchases.

In addition to product characteristics, we must have information on the underlyings of the structured products, as some of our analyses require a comparison with the return of the underlyings. Our initial data on SFPs contain the name of the underlying but lack information on the ISIN. As a first step to complete the list of underlying ISINs, we use data from Börse Stuttgart. This list, however, does not include a sufficient amount of securities, so the list had to be completed by hand. This combination results in a coverage of 97% of all underlyings. The remaining 3% belong to securities, which are traded by a very small number of investors or which are issuer-specific baskets of securities not traded in the market. The dominant underlying of SFPs is the DAX, which reflects 28% of all underlyings in terms of both the available ISINs and transactions. Summing over the nine next-dominant underlyings includes approximately 20% of all products. This calculation suggests that the ten most important underlyings include almost 50% of all products. All of these products are standard underlyings and are either international stock indices, exchange rates or large German stocks**.**

2.4 Trading characteristics of investors

2.4.1 General user properties

We seek to understand which investor characteristics and trading behaviors affect the probability of purchasing a particular type of structured financial product. To identify comparable results subject to investor characteristics, we run subsample analyses. In a first step, the final sample of investors can be divided into those who trade LSFPs at least once during the sample period (LSFP users) and those who do not (nonusers). To answer the question of whether specific characteristics determine trading, we provide the results from the descriptive analyses and, for robustness, the results from the linear probability models.

Table 2.3 compares the users of LSFPs (right panel) with the nonusers (left panel). The p-values report statistical significances and the results from the t-tests testing for differences in the means between the users and the nonusers. Compared with the nonusers, the users of LSFPs are more likely to be male (91% vs. 80%), to be less risk averse (average risk class of 4.57 vs. 2.96) and to have a higher portfolio value (54,148 vs. 43,000 euros), and these findings are statistically significant at the 1% level. This result corresponds with the results from Calvet et al. (2017), who document that SFP users are significantly wealthier in terms of their financial wealth, of which the portfolio value is a substantial part.

The LSFP users trade more heavily when we examine the average number of total trades (918 vs. 222). This difference does not result exclusively from trades in SFPs (440) but also results from trades in single stocks, which are more than twice as high as in the case of nonusers (375 vs. 123). In addition, 98% of the users trade single stocks, while only 88% of the nonusers trade this asset class.

The preference for single assets, the higher average risk class, the high concentration within their portfolios and the higher portfolio values suggest that users of LSFPs are rather sophisticated and have strong opinions about their investments. The higher number of trades shows that they are more experienced in investing, not only in LSFPs but also in general.

In addition to the univariate approach, the multivariate linear probability model considers the influence of demographic and trading characteristics on the probability of trading SFPs to check for the robustness of the univariate results. Table A 2.1 in the appendix is subdivided into three panels: on the left are SFP users who make at least one trade in SFPs during the sample period, in the middle are investors who make at least one trade in ISFPs during our sample period, and on the right are investors with at least one trade in LSFPs. Almost every variable has a significant influence on the probability of trading SFPs, with directions in line with those of the univariate analyses. For users of SFPs in general, and those of LSFPs in particular, the probability of trading these products is significantly higher for men. For every user classification, the probability of trading the associated products is higher when the risk aversion is smaller, the portfolio value is higher, and if the investor also trades stocks and funds. The portfolio diversification, in contrast, paints an ambiguous picture; it is higher for ISFP users while LSFP users seem to have less diversified portfolios. Thus, the results are in line with the previously described findings.[13]

[13] Applying logit regressions instead leads to comparable results.

Table 2.3: Descriptive statistics of LSFP users vs. nonusers

This table gives evidence on the descriptive statistics of the investors in our sample. The table covers the period from 2000 to 2015 and divides the investors into those who use LSFPs at least once during the sample period (users on the right hand side) and those who never used any LSFP (nonusers on the left hand side). For both user groups, the number of observations and the mean and median statistics are shown for variables concerning personal characteristics, trading characteristics, and the usage of the most important asset classes used by our sample investors. The two columns on the right display a difference in the mean analysis between users and nonusers.

		Investors not using LSFPs			Users of LSFPs				
		Observations	Mean	Median	Observations	Mean	Median	Delta	p-value
Personal & Portfolio Characteristics	**Unit**								
Gender (Female =1)	percent	38,909	0.20	0.00	22,077	0.09	0.00	-0.10	0.00
Risk Class (1 = most risk averse, max = 5)	category	38,909	2.96	3.00	22,077	4.57	5.00	1.61	0.00
HHI (1 = not diversified)	percent	38,909	0.20	0.13	22,077	0.27	0.20	0.07	0.00
Self-employed	percent	38,909	0.20	0.00	22,077	0.23	0.00	0.03	0.00
Age	years	38,909	52.71	51.00	22,077	53.03	52.00	0.32	0.00
Portfolio Value	Euros	38,909	43,000	27,231	22,077	54,148	30,354	11,148	0.00
Academic Title	percent	38,909	0.07	0.00	22,077	0.07	0.00	-0.01	0.01
Married	percent	38,909	0.59	1.00	22,077	0.58	1.00	-0.01	0.02
Trading Characteristics									
Number of Total Trades	count	38,909	222.28	111.00	22,077	918.36	478.00	696.07	0.00
Number of Trades in single stocks	count	38,909	123.43	33.00	22,077	374.59	152.00	251.16	0.00
Number of Trades in funds	count	38,909	91.83	18.00	22,077	95.57	22.00	3.74	0.02
Number of Trades in SFPs	count	38,909	3.49	0.00	22,077	440.12	98.00	436.62	0.00
Value of Trades in SFPs	Euros	38,909	264,200	0.00	22,077	2,362,422	307,032	2,098,223	0.00
Usage of Asset Classes									
Usage of single stocks (1 = one trade in stocks)	percent	38,909	0.88	1.00	22,077	0.98	1.00	0.10	0.00
Usage of funds (1 = one trade in funds)	percent	38,909	0.84	1.00	22,077	0.81	1.00	-0.02	0.00
Usage of ISFPs (1 = one trade in ISFPs)	percent	38,909	0.31	0.00	22,077	0.67	1.00	0.36	0.00
Usage of LSFPs (1 = one trade in LSFPs)	percent	38,909	0.00	0.00	22,077	1.00	1.00	1.00	0.00

2.4.2 Product usage over time

To further investigate investor trading in LSFPs, we assess their usage over time. In Figure 2.2 we can see that, between 2000 and 2008, the absolute number of SFP users per month, measured as the number of investors with at least one SFP in their portfolio in the corresponding month, increases sharply and reaches its maximum of more than 25,000 users in 2008 among the 60,986 investors in our sample. Even though this number decreases after 2008, it does not fall below 15,000 investors. This result suggests that the majority of 33,945 SFP users who trade at least one SFP during our sample period use these products repeatedly and periodically.

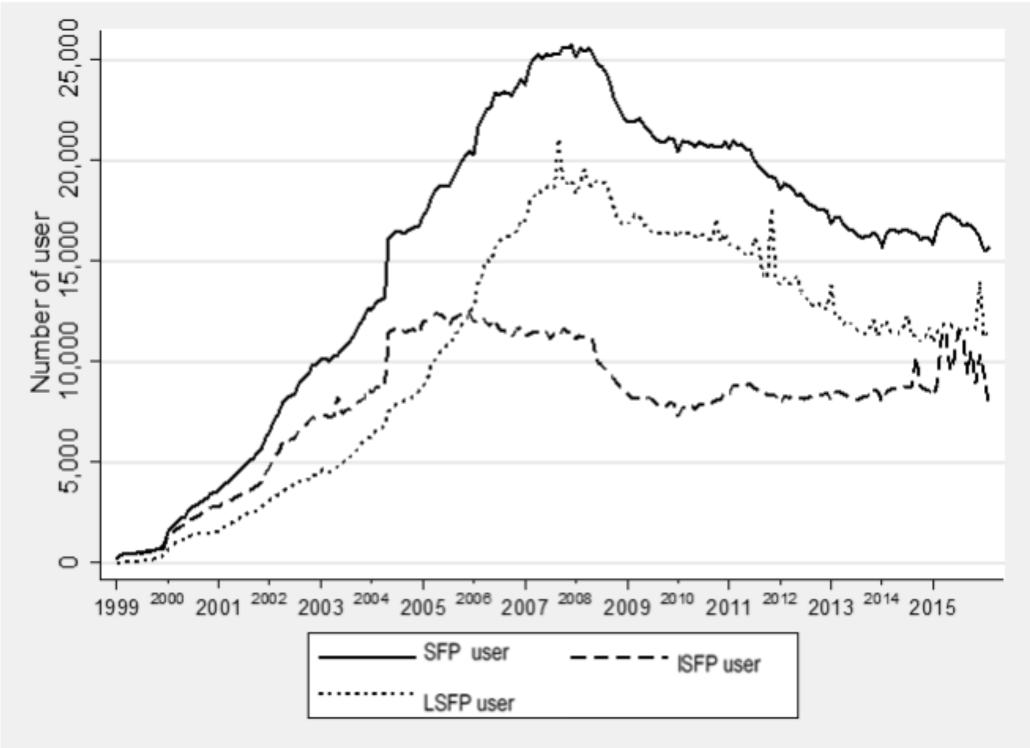

Figure 2.2: The number of SFP users over time

Figure 2.3 shows the portfolio share of all SFPs conditional on the usage of the SFP category in the respective month. The bold line shows the portfolio share of SFPs in terms of euros invested of only those portfolios that include at least one SFP in that month. The dotted line shows the portfolio share (in terms of portfolio value) for LSFPs. The share of SFPs increases between 2000 and 2008. Depending on use, LSFPs have a portfolio share of 25%. After the onset of the financial crisis, SFPs and LSFPs account for a smaller portion of portfolios. Even though SFPs consist of ISFPs and LSFPs, participation in both products cannot be summed to result in SFP usage. The reason is that investors use both product types simultaneously, so they would be counted twice.

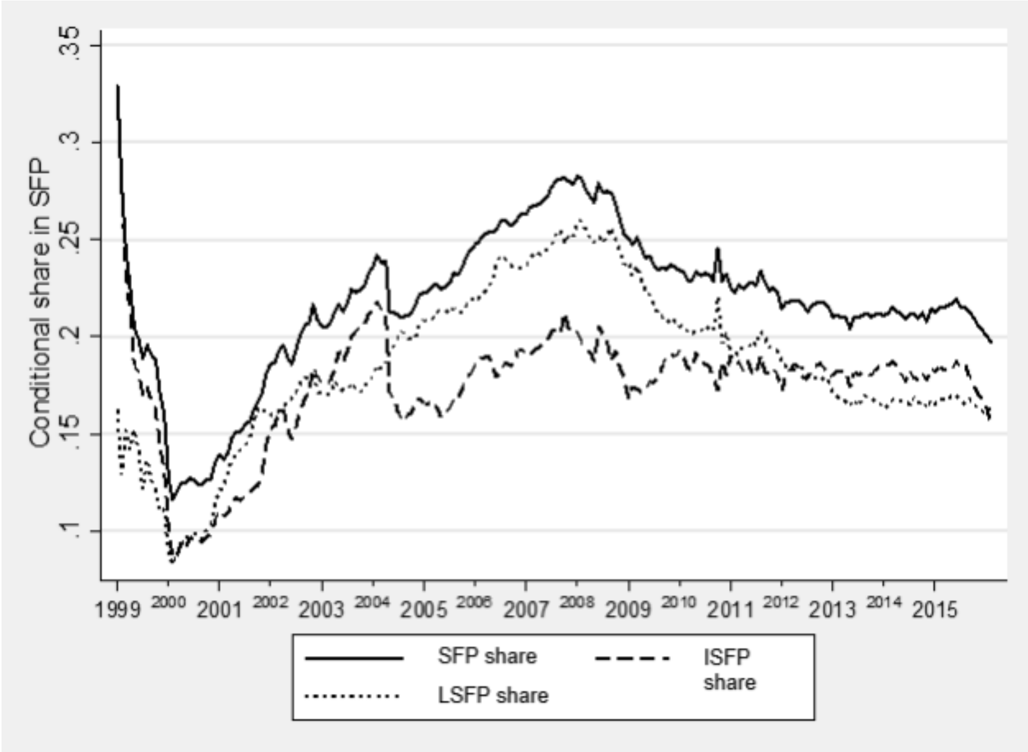

Figure 2.3: Portfolio share of SFPs depending on their usage

The previous literature on the investment behavior of private investors showed that many private investors behave as momentum or contrarian investors, which means they purchase after a rather good or bad previous performance, respectively (Barber & Odean (2008)). To account for the influence of the previous portfolio performance on the investment decisions of private investors in our sample, Table 2.4 shows the impact of previous portfolio returns on the purchase and sale decisions in SFPs and in the subgroups of ISFPs and LSFPs. Following previous research, we correct for data errors that lead to implausible portfolio values. Winsorizing at the 1.5 and 98.5 percentiles to control for large outliers slightly reduces the sample size.

$$Transaction_{i,t} = \left(Return_{i,t-1}, Portfolio\ Size_{i,t}, Flow_{i,t}, SD\ Return_{i,t-1}, I, T\right), \tag{2.1}$$

where $Transaction_{i,t}$ can be either a purchase or a sale. In line with the literature on mutual fund flows (Sirri & Tufano (1998)), we divide the previous 1-year portfolio returns ($Return_{i,t-1}$) into quintiles. The first quintile represents the 20% lowest returns in each month, and the fifth quintile reflects the 20% highest returns in each month. Additionally, the regression contains a set of control variables including the portfolio size, a flow variable for flows into the portfolio of investor i compared to the previous month, the previous year standard deviation of investor i's portfolio, and person (I)- and year (T)-fixed effects.

Table 2.4: The impact of past performance on the trading behavior in SFPs

This table shows a linear probability model that tests for the effect of previous year portfolio returns on the probability of purchasing or selling SFPs (on the left), ISFPs (in the middle) and LSFPs (on the right) in this month. This analysis follows Sirri & Tufano (1998) in that the previous 1-year portfolio returns are divided into quintiles. The first quintile represents the 20% lowest returns, and the fifth quintile reflects the 20% highest returns in each month. Every specification includes control variables on the portfolio size, the amount of inflows to the portfolio, the return standard deviation of the previous year, and the year- and person-fixed effects. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	SFPs		ISFPs		LSFPs	
	Purchase	Sale	Purchase	Sale	Purchase	Sale
Quintiles of the portfolio return of the previous year						
1. Quintile	0.015***	0.026***	0.011***	0.021***	0.007***	0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
2. Quintile	0.003***	0.004***	0.001***	0.001***	0.003***	0.003***
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
4. Quintile	0.000*	0.001***	0.001***	0.001***	-0.001***	-0.001**
	(0.065)	(0.000)	(0.000)	(0.000)	(0.008)	(0.016)
5. Quintile	0.006***	0.008***	0.008***	0.008***	0.001**	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)	(0.000)
Control Variables						
Portfolio Size	0.008***	0.007***	0.004***	0.003***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Flow	0.112***	-0.041***	0.064***	-0.028***	0.034***	0.022***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Return SD previous year	5.400***	9.669***	6.883***	11.531***	-0.046	-0.974***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.583)	(0.000)
Year-Fixed Effects	YES	YES	YES	YES	YES	YES
Person-Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	7,024,953	7,024,953	7,024,953	7,024,953	7,024,953	7,024,953
R-squared	0.109	0.095	0.135	0.128	0.065	0.063

The probability of purchasing or selling SFPs in general and ISFPs in particular depends on the previous year's return and is U-shaped. Investors more actively trade in these products if the previous year's portfolio return is low (quintile 1) or high (quintile 5). In contrast, the probability of trading LSFPs is the highest after low past returns (quintile 1). These results suggest that private investors take into account their own past performance when making investment decisions in SFPs.

2.5 Performance assessment

2.5.1 Round trip performance

Round trip returns are the realized returns computed from the day and price of purchase to the day and price of sale. Therefore, round trip returns take into account the holding periods of investors, which can differ greatly between asset classes. In addition, this calculation uses actual prices and allows transaction costs to be included or excluded. This form of investigation has some disadvantages, as the outcomes are biased upwards for two reasons. First, the disposition effect results in positively skewed returns. This effect was initially shown by Shefrin & Statman (1985) and states that investors sell good-performing assets too early while holding on to bad-performing assets. Second, products that are knocked out or that are not sold until the end of the sample period may be ignored, since they do not contain an actual sale, they do not appear in the transactions.

Despite the described disadvantages, round trips are reasonable to use, since they reflect realized transactions, and to carefully account for knocked out securities or those that remain in portfolios in separate analyses to obtain a complete overview.

To begin with the investigation of round trip returns, Table 2.5 depicts the round trip returns of all investors in our sample between 2000 and 2015 in the following three security types: stocks, ISFPs and LSFPs. This table provides several insights: on the one hand, the differentiation between gross and net returns for different security types and the duration of these transactions; on the other hand, a comparison of LSFP and ISFP returns with the return of the respective underlying.

First, LSFPs generate better returns than stocks and ISFPs. The average gross return of LSFPs is 1.5%, and the median is even higher, at 2.6%. Surprisingly, ISFPs, which aim to protect capital, have the smallest gross returns (0.08%). In contrast, LSFPs have a very small average loss, net of transaction costs, of -0.7% and a positive median net return of 1.25%, implying that more than half of all completed round trips yield positive returns. In addition, while the 25% quantile exhibits large losses, irrespective of the transaction costs, the 75% quantile suggests that one quarter of all round trips realize more than a 14% net return.

Table 2.5: Descriptive statistics on round trip returns of all investors in security types

This table reports the results from the round trip returns of all investors in our sample over the sample period 2000 to 2015 for stocks, ISFPs and LSFPs both gross and net of transaction costs. Round trip returns measure the actual outcome of a completed transaction, computing the difference between the price of purchase and the price of sale. To determine whether it would have been better to buy the underlying instead of the SFP, for ISFPs and LSFPs the gross and net returns of the corresponding underlying and round trip are also shown.

		Round Trip Returns of all Investors				
		Observations	Mean	Median	25%	75%
Stocks						
	Gross Return	26,900,000	0.23%	0.89%	-11.11%	10.63%
	Net Return	26,900,000	-1.48%	-0.05%	-13.01%	9.09%
	Duration	26,900,000	176.38	30	6	144
ISFP						
	Gross Return	1,289,358	0.08%	0.59%	-9.05%	8.52%
	Net Return	1,289,358	-2.99%	-1.07%	-12.13%	5.31%
	Gross Return Underlying	1,087,924	6.44%	1.75%	-4.75%	13.43%
	Duration	1,289,358	254.86	94	20	300
LSFP						
	Gross Return	16,700,000	1.54%	2.61%	-13.76%	16.61%
	Net Return	16,700,000	-0.70%	1.25%	-15.97%	14.18%
	Gross Return Underlying	16,600,000	0.67%	0.00%	-0.01%	0.78%
	Duration	16,700,000	15.14	2	1	7

The round trip duration differs greatly, ranging from, on average, 255 days for ISFPs, which are part of a buy and hold strategy, to an average (median) duration of completed trades of 15 (2) days of trades in LSFPs. These products are frequently traded. Thus, a substantial cause of the weak net performance in LSFPs might be the high turnover.

A comparison of the returns of ISFPs and LSFPs with the returns of the respective underlying of each trade answers the question whether it would have been better to directly invest in the underlying instead of the structured product. While ISFPs generate a small positive return before and a large negative return after transaction costs, buying the corresponding underlyings instead would have yielded positive average gross returns. This discrepancy might originate from the protective goals of ISFPs, which demand a premium and thus lower the return. In contrast, LSFPs have an almost 1 percentage point higher gross return than the underlying of the trade. Consequently, investing in the LSFPs instead of making a direct long investment in the underlying over the same investment horizon seems to benefit investors.

Unclosed positions, either knocked out LSFPs or products that remain in the portfolio at the end of our sample period, account for 6% of all round trips in SFPs. More closely investigating the underlyings of knocked out or not sold products reveals that neither the underlying nor the structure of the product shows any abnormalities. Of these products, 36% have a DAX underlying. The subsequent nine most prevalent underlyings account for 24% of all products and are based on international indices, exchange rates and large German stocks. In addition, approximately 97% of the unclosed transactions are based on LSFPs with 2 scenarios, which is also the most dominant structure of all closed round trips.[14] Thus, the unclosed transactions have underlyings and characteristics that are quite similar to those of products in the closed round trips in general.

Table 2.6 depicts the round trip returns for all investors in unclosed product positions, divided by security type. Especially for LSFPs, unclosed positions have a large average loss of 43%, which might stem from product terminations. However, not all of these positions result in a total knock out, which would have generated a return of -100%.[15]

Given that these unclosed positions are missing in the previous return analyses, an overall performance assessment must combine the results to evaluate security types. Weighting the returns by the number of observations in complete and incomplete round trips (last column of Table 2.6) results in a negative performance for stocks, ISFPs and LSFPs.

Before the transaction costs, LSFPs have fewer negative returns than stocks (-0.79% vs. - 1.28%). This result suggests that, on a per trade basis, the performance of LSFPs is quite similar to the performance of other products.

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[14] The products and scenarios will be shown in more detail in Section 2.5.3.

[15] The numbers for stocks and ISFPs indicate an investment mistake that has been shown to negatively affect the performance of household investments. The disposition effect (Shefrin & Statman (1985)) is the tendency to maintain badly performing securities in the portfolio. The large negative positions in stocks with losses of more than 16% reflect this effect.

Table 2.6: Descriptive statistics on round trip returns of knocked out or not sold products

This table shows the round trip returns of incomplete transactions, which are either knocked out products or positions remaining open at the end of the sample period ranging from 2000 to 2015. Since these transactions are incomplete, it is not possible to give information on the duration of these holdings.

	Round Trip Returns of of knocked out products			Combined returns (completed and knocked out round trips):
	Observations	Mean	Median	
Stocks				
Gross Return	2,729,396	-16.17%	-15.55%	-1.28%
Net Return	2,729,396	-16.30%	-15.72%	-2.85%
ISFP				
Gross Return	284,831	-1.74%	1.05%	-0.25%
Net Return	284,831	-2.47%	0.66%	-2.90%
LSFP				
Gross Return	913,332	-43.41%	-54.55%	-0.79%
Net Return	913,332	-43.46%	-54.59%	-2.92%

Even though the performance of investments in LSFPs differs, generating large positive rewards for the best performing investments – combining all positions, on average – these products do not seem to benefit the average private investor. However, comparing the returns to those of the other products in this analysis, on average, LSFPs offer higher positive (completed round trips) and fewer negative outcomes (after including knock outs) than stocks.

2.5.2 Counterfactual portfolios

In addition to the trade-based perspective, which comes from the round trip analyses, we want to test the robustness of our results by focusing on portfolio performance. To do so, we build counterfactual portfolios (CF), which include different specifications.

i. Full portfolio: includes all assets actually contained in the portfolio
ii. Portfolio without LSFPs: excludes all LSFPs from the portfolio
iii. Portfolio without ISFPs: excludes all ISFPS from the portfolio

Regressing the portfolio with all assets, including SFPs, on the portfolio without different specifications of SFPs allows for testing whether a difference is statistically significant and for testing some conjectures about the reasons why the differences exist. The regression is as follows:

$$r_{i,t,CF} - r_f = \alpha + \beta\left[r_{i,t,no\ SFP} - r_f\right] + I + \varepsilon, \tag{2.2}$$

where $r_{i,t,CF}$ is the portfolio return of investor i in month t for one of the counterfactual portfolio specifications, CF. Variable $r_{i,t,no\ SFP}$ reflects the portfolio return of investor i for all products other than SFPs. We proxy the risk-free rate by the 3-months euro cash and variable I includes investor-fixed effects. The advantage of using the counterfactual portfolio approach is that we compare within the same investor, thereby mitigating self-selection and endogeneity issues from which a between-person design might suffer. All of the following discussions aim at measuring the marginal effect of SFP positions on portfolio performance. In these regressions, standard errors are clustered at the portfolio ID.

The results of the regressions depicted in Table 2.7 show the gross and net portfolio performance in excess of the risk-free rate. The main variable is the constant, which reflects the excess return p.a. of the variable of interest relative to the return of the portfolio without the respective SFP specification. SFPs decrease the annual portfolio return by 1.6 percentage points before transaction costs. The greatest part of this effect stems from LSFPs, which account for 1.4 percentage points, while ISFPs have only a small contribution to overall portfolio performance. Considering the investor-fixed effects in the right panels to account for the extreme return events of single investors does not alter the results.

The comparison between gross and net returns (Panel A and B) suggests that trading in LSFPs is more expensive to customers than trading in other securities as the contribution increases by approximately 100 basis points p.a. Investors trading more in these securities likely drive this result. However, the larger part of the difference already exists before considering transaction costs.

Table 2.7: Gross and net portfolio performance of all investors

This table shows the results of a market model, in which three SFP specifications are separately regressed on the difference between the portfolio return and the risk-free rate (3-month euro Cash) on a daily basis. Thereby, Panel A shows the gross and Panel B the net returns. The "Full portfolio" specification includes all products; thus, the constant, which is annualized, displays the contribution of SFPs to the portfolio return. The specifications "LSFP contribution" and "ISFP contribution" divide the former effect and indicate how the portfolio return alters if these products are included. The three columns on the left do not have any control variables; the analyses depicted on the right include investor-fixed effects. Robust p-values are in parentheses, and ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	Full portfolio	LSFP contribution	ISFP contribution	Full portfolio	LSFP contribution	ISFP contribution
			Panel A: Gross returns			
Gross return (no SFP)	0.971	0.999	0.968	0.970	0.998	0.968
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Constant (per annum)	-0.016	-0.014	-0.003	-0.016	-0.014	-0.003
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Observations	7,819,105	7,819,106	7,819,105	7,819,105	7,819,106	7,819,105
R-squared	0.823	0.841	0.971	0.823	0.841	0.971
			Panel B: Net returns			
Net return (no SFP)	0.973	1.001	0.969	0.970	0.998	0.968
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Constant (per annum)	-0.028	-0.025	-0.004	-0.028	-0.025	-0.004
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Observations	7,819,103	7,819,104	7,819,103	7,819,103	7,819,104	7,819,103
R-squared	0.820	0.838	0.971	0.821	0.839	0.970
Investor-fixed effect	NO	NO	NO	YES	YES	YES
Number of portfolio ID				56,261	56,261	56,261

2.5.3 Robustness tests

Potential determinants of the LSFP portfolio contribution

Additional tests aim to identify the potential reasons for the negative portfolio contribution of LSFPs. Thus, we rerun the analysis of Equation (2.2) adding different sets of additional factors.

Two of the additional factors can reduce the negative portfolio contribution of LSFPs. Previous research has shown that investment mistakes diminish with increasing experience (Feng & Seasholes (2005)). To control for this factor, in this specification we include only investors with at least 24 months of experience (Table A 2.2). This calculation reduces the negative net portfolio contribution of LSFPs from 2.5 to 1.6 percentage points p.a.

A well-known measure to account for overconfidence, which can negatively affect portfolio performance, is the turnover in an investor's portfolio (Barber & Odean (2001), Kumar (2009), Grinblatt & Keloharju (2009)). We therefore exclude the 25% of investors with the highest turnover (Table A 2.3). By doing so, the negative net contribution of LSFPs is reduced to 1.4 percentage points p.a.

In unreported analyses, we test for market-timing following Henriksson & Merton (1981), exclude the second half year of 2008 to account for the effect of Lehmann Brothers or take into account recessions in the euro area, control for momentum (Carhart (1997)) and exclude investors whose portfolios have an average value smaller than 5,000€ to account for gambling (Kumar (2009)). These adjustments do not qualitatively alter the negative portfolio contribution of LSFPs; thus, they do not seem to be important drivers of performance.

These tests show that none of the factors alone explains the underperformance of investors driven by LSFPs. However, the tests suggest that the underperformance seems to be driven by the trading decisions of investors. Thereby, little experience and excessive trading in products seem to be the most promising sources of explanation.

Product complexity

Headed by Barber & Odean (2008), empirical studies focus on the effect of limited attention on investment behavior. While many papers provide evidence of problems during the search process when entering new positions, Blonski & Blonski (2016) use a survey to show that retail investors lack the mathematical knowledge to correctly understand and interpret complex payout profiles, such as those of LSFPs. This result would suggest that the complexity of LSFPs determines their performance, as understanding the product is indispensable to forming reasonable expectations and consequently to performing well.

The product specifications indicate deviating levels of complexity of single LSFP types. Following Célérier & Vallée (2017), we measure the complexity by counting the number of scenarios for each product. The only LSFP with 1 scenario is a factor certificate, included in 1.5% of all trades, which participates in the performance of the underlying with a factor greater than one. In terms of the level of completed round trips, products with 2 scenarios account for almost 98% of all trades. The most prominent product with 2 scenarios is a classic warrant, which offers two potential scenarios. If the price of the underlying does not breach the predefined barrier during the product lifetime, the investor receives a positive return, which is a multiple of the return of the underlying. Otherwise, the investor faces a loss that is limited to his initial investment. Of all trades, 0.6% are in products with 3 scenarios, e.g., inline warrants that pay a predefined amount only if the price of the underlying does not leave a certain corridor during the product lifetime. If it is above the upper or below the lower barrier just once, the security expires worthless. A very small number of trades are in products with 4 scenarios.

Table 2.8 divides LSFPs into groups based on the number of scenarios in their payout profiles. Surprisingly, the performance does not linearly depend on the complexity of a product. In fact, round trips in products with 4 scenarios show the highest net returns among all products. In addition, factor certificates, which are the only LSFPs with just one scenario, have by far the worst gross return of -3.35%. For these products, an investment in the underlying would have been better, which is reasonable as the factor certificate reflects the performance of the underlying multiplied by a factor greater than one. Thus, if investor expectations about the future performance are incorrect, they lead to a multiple of the loss of the underlying product (limited to the initial investment).

Table 2.8: Descriptive statistics on round trip returns of LSFP investors for different levels of product complexity

This table shows descriptive statistics on the round trip returns of LSFP users, controlling for the number of LSFP payout scenarios. The scenarios in a payout function are used as a measure of product complexity. While with one scenario, the payout function has no kink (the outcome is a multiple of the performance of the underlying), products with more scenarios offer diverging paths of payout subject to the performance of the underlying.

	Round Trip Returns of LSFP Investors				
	Observations	Mean	Median	25%	75%
1 Scenario					
Gross Return	253,179	-3.35%	0.46%	-15.03%	9.55%
Net Return	253,179	-6.20%	-1.37%	-17.71%	6.79%
Gross Return Underlying	246,672	1.07%	0.00%	-1.76%	3.20%
Duration	253,179	34.86	9.00	3.00	30.00
2 Scenarios					
Gross Return	16,200,000	1.72%	2.70%	-13.64%	16.76%
Net Return	16,200,000	-0.51%	1.35%	-15.82%	14.40%
Gross Return Underlying	16,100,000	0.67%	0.00%	0.00%	0.73%
Duration	16,200,000	14.12	2.00	1.00	6.00
3 Scenarios					
Gross Return	98,787	0.12%	2.77%	-17.53%	17.36%
Net Return	98,787	-1.35%	1.75%	-19.07%	15.65%
Gross Return Underlying	97,318	0.96%	0.01%	-1.78%	3.32%
Duration	98,787	28.27	11.00	4.00	31.00
4 Scenarios					
Gross Return	2,781	1.44%	5.04%	-7.82%	11.65%
Net Return	2,781	0.41%	4.38%	-8.39%	10.80%
Gross Return Underlying	2,781	0.82%	0.65%	-1.50%	3.56%
Duration	2,781	20.26	10.00	4.00	24.00

2.6 Trading motives of LSFP investors

In a next step, we divide the sample of LSFP users into three groups based on the direction and duration of their trades and their portfolio compositions. The following illustration provides an overview of the trader types. Following this classification, 45% of the investors are dynamic hedgers, 25% are hedgers and 30% are speculators.

Leverage		Short	Long
	Positive	with equity: *Speculator* without equity: *Speculator*	with equity: *Dynamic hedger* without equity: *Dynamic hedger*
	Negative	with equity: *Hedger* without equity: *Speculator*	with equity: *Hedger* without equity: *Speculator*
		Duration	

Figure 2.4: Investor classifications based on round trip duration, leverage and portfolio composition

Hedgers are required to have a positive equity share in their portfolios,[16] which they want to protect with short positions in LSFPs.[17] These positions aim to prevent investors from losing money with their direct investments. In return, investors must accept the costs that come with hedging in that they lower their returns from a portfolio perspective.

The second group of investors we find has longer investment horizons and positive leverage. These investors focus on buy-and-hold strategies in LSFPs that offer the possibility of disproportionately profiting from rising asset prices in the long term. We label them dynamic hedgers.

[16] If investors want to hedge positions using LSFPs, they need to have direct positions in the underlying as well. The analysis of underlying investments showed that the majority of them comprise well-known equity positions or equity indices. We use this knowledge to approximate the underlying by splitting investors subject to having a positive equity share or not having equity positions in their portfolios. Therefore, every trade that aims to hedge requires an investor to have a positive equity share at the end of the month before an SFP transaction takes place. We consider indirect equity investments in mutual funds based on the peer-group in which the fund is trading.

[17] The direction of leverage is based on the movement of the LSFP relative to the movement of its underlying over the longest observable time period.

All of the remaining combinations classify an investor as a speculator, either because the duration is rather short or because the portfolio has no positive equity share. All of these positions are open to yield returns by actively trading LSFPs.

As these investor groups seem to have different trading motives, the next step is to analyze whether they differ in their personal and investment characteristics. Table 2.9 provides the descriptive statistics of LSFP investors by investor classification. We find large differences, especially for their portfolio values and trading characteristics. The two hedger groups have average portfolio values of approximately 60,000 euros, whereas the portfolios of speculators, on average, amount to a size of 38,616 euros. In addition, the former have HHI values of 0.22 and 0.23, which reflect quite diversified portfolios.[18] For speculators, the HHI is 0.36; thus, their portfolios are, on average, less diversified. These differences become even more evident in the case of the average number of trades executed during our sample period. With, on average, 1,361 trades, speculators are almost twice as active as hedgers and dynamic hedgers. The average risk class of speculators is higher as well, indicating lower risk aversion.[19]

[18] The HHI measures the amount of concentration. A highly diversified portfolio does not show any concentration; therefore, the index is close to zero. In contrast, a portfolio with very few different single assets is highly concentrated, which is demonstrated by a HHI close to one.

[19] Results from a multivariate linear probability model in Table A 2.4 in the appendix confirm these findings.

Table 2.9: Descriptive statistics of LSFP investors by investor group

This table shows the descriptive statistics of three LSFP user groups defined by the duration and direction of their round trips and by the equity shares in their portfolios. Dynamic hedgers are investors who have positive levels of leverage and a long-term perspective in their trades. Hedgers have a positive equity share and engage in LSFPs to protect these investments from large losses. Speculators do not have corresponding equity positions but use LSFPs as a stand-alone instrument to invest strategically. For all user groups, the number of observations and the mean and median statistics are shown for variables concerning personal characteristics, trading characteristics and the usage of the most important asset classes used by our sample investors. The sample period lasts from January 2000 until December 2015.

		Dynamic Hedger			Hedger			Speculator		
		Observations	Mean	Median	Observations	Mean	Median	Observations	Mean	Median
Personal & Portfolio Characteristics	**Unit**									
Gender (Female =1)	percent	9,756	0.10	0.00	5,380	0.09	0.00	6,941	0.08	0.00
Risk Class (1 = most risk averse, max = 5)	category	9,756	4.47	5.00	5,380	4.54	5.00	6,941	4.72	5.00
HHI (1 = not diversified)	percent	9,756	0.22	0.16	5,380	0.23	0.17	6,941	0.36	0.30
Self-employed	percent	9,756	0.22	0.00	5,380	0.22	0.00	6,941	0.25	0.00
Age	years	9,756	53.97	53.00	5,380	52.64	51.00	6,941	52.00	51.00
Portfolio Value	Euros	9,756	62,291	36,168	5,380	59,418	33,918	6,941	38,616	19,273
Academic Title	percent	9,756	0.07	0.00	5,380	0.07	0.00	6,941	0.05	0.00
Married	percent	9,756	0.60	1.00	5,380	0.59	1.00	6,941	0.55	1.00
Trading Characteristics										
Number of Total Trades	count	9,756	669.10	392.00	5,380	799.45	435.00	6,941	1,360.86	700.00
Usage of Asset Classes										
Usage of single Stocks (1 = one trade in stocks)	percent	9,756	0.98	1.00	5,380	0.99	1.00	6,941	0.97	1.00
Usage of SFPs (1 = one trade in SFP)	percent	9,756	1.00	1.00	5,380	1.00	1.00	6,941	1.00	1.00

Table 2.10 shows data on the return of LSFP user groups. On the left hand side, the table shows the mean and median returns of completed round trips. The returns on the right side combine complete and incomplete transactions by weighting the outcomes by the number of observations. For both specifications, hedgers have a negative return (-3.28% before and -6.21% after including knock outs but before transaction costs), which can be considered to be an insurance premium. Dynamic hedgers have positive gross returns, which yield 5.15% per completed round trip and 1.01% after knock outs. Speculators also have positive gross returns, amounting to 1.63% before and 0.11% after including terminated positions.

Table 2.10: Descriptive statistics of LSFP user group returns in LSFPs

This table shows the descriptive statistics on the return of the completed round trips of the LSFP user groups and on the combined returns, including knocked out or not properly closed transactions weighted by the number of observations. Round trip returns measure the actual outcome of a completed transaction, computing the difference between the price of purchase and the price of sale.

		Completed Round Trips			After knock outs
		Observations	Mean	Median	
Dynamic Hedger					
	Gross Return	3,549,543	5.15%	7.67%	1.01%
	Net Return	3,549,543	2.86%	5.45%	-1.12%
Hedger					
	Gross Return	2,860,110	-3.28%	-0.40%	-6.21%
	Net Return	2,860,110	-5.56%	-1.99%	-8.34%
Speculator					
	Gross Return	10,300,000	1.63%	2.36%	0.11%
	Net Return	10,300,000	-0.58%	1.15%	-2.01%

When separately examining the return of LSFP user groups for every year of our sample period in Figure 2.5, we find large differences between the groups and years. Hedgers (light gray bars) generated positive gross returns only in 2008, which might be interpreted as insurance against the immense market drop in the financial crisis. However, in all of the other years, the strategy used by hedgers did not benefit them, even though markets also lost value in some other years.[20] In contrast, dynamic hedgers (white bars) who follow the market movement subject to their positive leverage yielded negative returns in the beginning of the sample period and in 2008. For many of the other years, dynamic

[20] The following years display a negative development of the DAX, the most frequent underlying of our investors, from January to December, 2000, 2001, 2002, and 2011.

hedgers had outcomes that were large and positive, even after including knocked out or incomplete round trips. Speculators (dark gray bars) had negative returns, especially in the first two years when the LSFP market was still very young, with few investors and products. Afterwards, speculators generated small positive and negative returns with no clear trend.

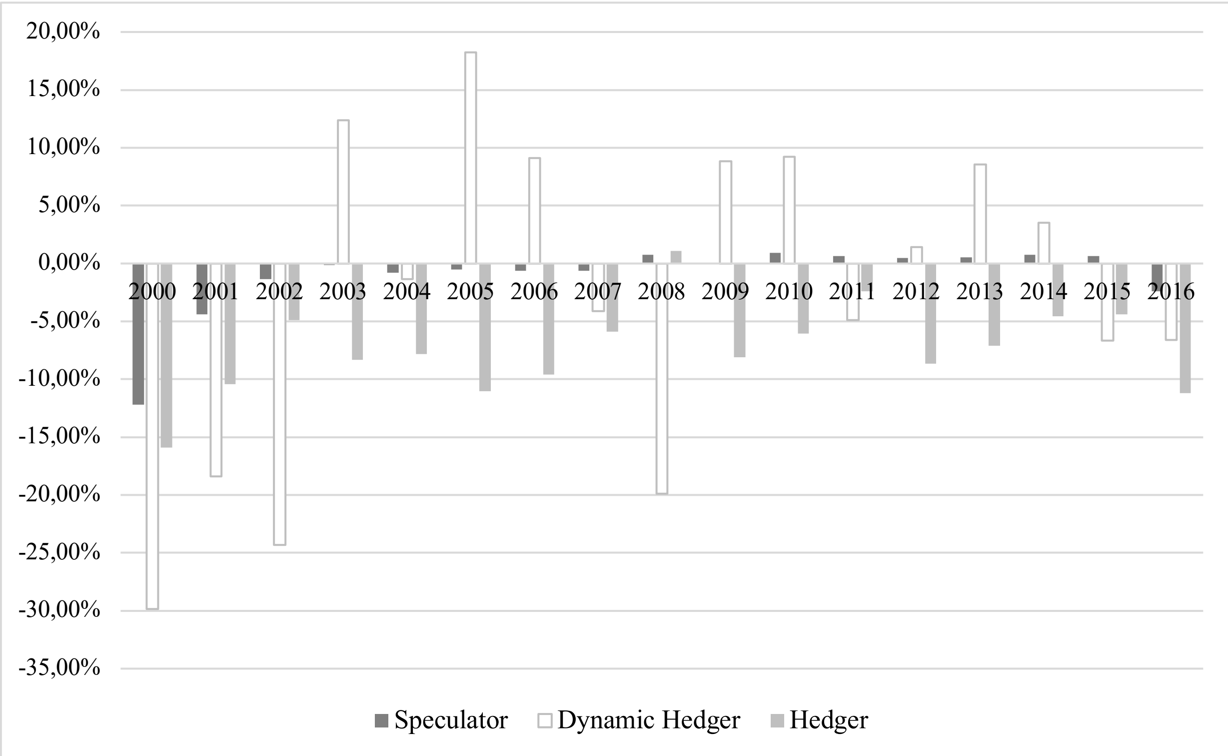

Figure 2.5: Gross round trip returns including the knocked out or incomplete transactions of LSFP user groups for each year

These differences between the groups and sample years provide evidence for LSFPs in general as products that can positively affect investment outcomes if they are used deliberately, as shown by dynamic hedgers. Of course, the actual outcome depends on the performance of the underlying, but, in general, trading less and with a more long-term perspective offers the chance to generate high profits. The overall large negative returns of hedgers, who generated positive outcomes only in 2008, raise the question whether it is reasonable to hedge large parts of the portfolio using LSFPs except for during periods in which investors expect severe market crashes.

2.7 Conclusion of Chapter 2

The goal of this study was to answer the questions of who trades LSFPs, how the performance in LSFPs is, and why investors trade these products. More than 35% of the sample investors trade LSFPs at least once during our sample period, ranging from 2000 to 2015. Most of these investors frequently use these products, and they account for a significant share of the users' portfolios. This finding suggests that, at least among investors at online brokerages, SFPs, and particularly LSFPs, are an important asset class. Both the personal and investment characteristics of LSFP users suggest that they know what they are doing and have strong opinions about their trades.

Compared with both the underlyings and with other products, completed round trips in LSFPs do not harm investors. Adding product terminations and unclosed positions to the analysis results in slightly negative LSFP returns of -0.79% after product but before transaction costs, which are less negative than comparable stock returns (-1.28%). However, LSFPs seem to negatively affect the full portfolio performance, which is mainly driven by trading rather than by product characteristics.

Dividing LSFP users by the dominant motive of their trades gives evidence that hedging is the main determinant of the negative performance. Hedging seems to make sense only if investors expect large market drops; otherwise, the premium paid is too high. Dynamic hedgers and speculators can generate positive returns before transaction costs are incurred.

At first glance, SFPs, and especially LSFPs, might appear to harm private investors because of their negative overall returns, so the logical consequence would be to prohibit them or to restrict some of the products. This consequence would be reasonable only if they could not benefit any retail investor. However, this paper shows that a group of investors uses LSFPs rationally and obtains high positive rewards before incurring transaction costs. The negative returns seem to stem from hedging and trading costs rather than from the products themselves.

Instead of prohibiting products in general, investors might experience better performance from bearing in mind the transaction and product costs that come with trading LSFPs. As these products are short-term instruments, whose maturities range from the end of the same day to several days or weeks, the high costs per completed transaction consume the initial positive returns. In addition, investors might need to be better informed about the costs associated with frequent trading because small stakes face the risk of not yielding sufficient rewards to result in a positive outcome after transaction costs.

Moreover, and most importantly, it would be reasonable to improve educational work on how to invest in financial products. For example, in the case of hedging transactions using LSFPs, even though these transactions aim at reducing portfolio risk by insuring parts of the portfolio outcome against large capital market slumps, the overall performance is negative. Thus, investors entering these positions should become aware of the trade-off between paying large (and, in most cases, unnecessary) insurance premiums and being hedged against market crashes.

However, this situation is necessary not only for complex products, such as LSFPs, but also for investments in general. As this study and previous research show, some investment mistakes investors make are independent from the actual product or security type. Therefore, rather than trying to regulate particular products, investors would obtain better yields if they held more diversified and long-term portfolios with less active trading. In addition, to obtain an understanding of the effect a new investment has on the existing portfolio, a tool that provides information on the potential risk-return profile of the portfolio after including a new asset might be helpful. In this way, investors would be better informed before they implement a new strategy, and some mistakes might be mitigated.

Chapter 3: Business cycle variations in exchange rate correlations: Revisiting global currency hedging

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Appendix

Table A 1.1: List of variables

This table contains the variables used in the analyses. The upper part shows different specifications of the dependent variable reflecting abnormal private investor trading. In the second panel, the explanatory variables on monetary policy are described and the last section gives information on the control variables included in the analyses.

Variable	Description
Dependent Variables	
ExBS (#)	Excess buy-sell imbalance of individual i at day t relativized with the average buy-sell imbalance of the corresponding year, in terms of the number of transactions
ExBS (EUR)	Excess buy-sell imbalance of individual i at day t relativized with the average buy-sell imbalance of the corresponding year, in terms of the monetary value of transactions
Explanatory Variables	
expected pre-crisis	Contains expected changes of the main refinancing rate of the ECB before 22 August 2007; expectations are included in terms of the 3-month futures rates on the Euribor, where expected changes are defined as being the difference between the actual change and the unexpected one
unexpected pre-crisis	Contains unexpected changes of the main refinancing rate of the ECB before 22 August 2007; expectations are included in terms of the 3-month futures rates of the Euribor, where unexpected changes are defined as being the difference between the futures rate of the day following and the day of an announcement
expected crisis	Contains expected changes of the main refinancing rate of the ECB between 22 August 2007 and 4 July 2012; expectations are included in terms of the 3-month futures rates on the Euribor, where expected changes are defined as being the difference between the actual change and the unexpected one
unexpected crisis	Contains unexpected changes of the main refinancing rate of the ECB between 22 August 2007 and 4 July 2012; expectations are included in terms of the 3-month futures rates of the Euribor, where unexpected changes are defined as being the difference between the futures rate of the day following and the day of an announcement
unexpected unconventional	Unconventional monetary policy of the ECB starts on 22 August 2007 with the first announcement of expansive monetary policy without actually changing the main refinancing rate, e.g. monetary easing; these decisions rate as unexpected if the spread between the 10-year government bond yield of Italy and Germany changes
expected ZLB	Contains expected changes of the main refinancing rate of the ECB after 5 July 2012 when the rate of deposit facility of the ECB hit the 0% boundary; expectations are included in terms of the 3-month futures rates on the Euribor, where expected changes are defined as being the difference between the actual change and the unexpected one
unexpected ZLB	Contains unexpected changes of the main refinancing rate of the ECB after 5 July 2012 when the rate of deposit facility of the ECB hit the 0% boundary; expectations are included in terms of the 3-month futures rates of the Euribor, where unexpected changes are defined as being the difference between the futures rate of the day following and the day of an announcement
unexpected unconventional ZLB	Unconventional monetary policy of the ECB after 5 July 2012 when the rate of deposit facility of the ECB hit the 0% boundary; these unconventional decisions rate as unexpected if the spread between the 10-year government bond yield of Italy and Germany changes

(continued)

Controls	
investor related variables	investor-fixed effects (by regression), log wealth
market-fixed effects	Includes 1-day returns, squared 1-day returns and 3-month returns of the CDAX
day-fixed effects	Contains national holidays and vacations, daylight savings, first and last day of the week and the month, and days with closed exchanges
month-fixed effects	Controls for every month of the year omitting December
year-fixed effects	Controls for every year of the dataset omitting 2015

Table A 2.1: Linear probability model with SFP usage as dependent variable

This table displays the results of a linear probability model, which tests the influence of personal and trading characteristics of sample investors on the probability to trade SFPs. Columns 1 to 4 consider SFPs in general, columns 5 to 8 and columns 9 to 12 show the effects on trading ISFPs and LSFPs, respectively. The gender variable is defined to be one if gender is female, risk class is a variable by which investors indicate their risk tolerance with 5 being the least risk averse and HHI measures portfolio concentration, where higher numbers result in higher concentration and consequently less diversification. There are standard errors in parentheses and ***, **, * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	SFP users: At least one SFP trade				ISFP users: At least one ISFP trade				LSFP users: At least one LSFP trade			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Gender (1=Female)	-0.1304***	-0.0349***	-0.0292***	-0.0169***	-0.0692***	-0.0019	-0.0068	0.0043	-0.1749***	-0.0739***	-0.0628***	-0.0518***
	(0.0055)	(0.0049)	(0.0049)	(0.0049)	(0.0055)	(0.0053)	(0.0052)	(0.0051)	(0.0053)	(0.0046)	(0.0046)	(0.0046)
Risk Class (min = 1, max = 5)		0.1463***	0.1433***	0.1337***		0.1030***	0.0986***	0.0887***		0.1547***	0.1536***	0.1441***
		(0.0012)	(0.0012)	(0.0012)		(0.0013)	(0.0012)	(0.0013)		(0.0011)	(0.0011)	(0.0011)
ln (Portfolio Value)			0.0276***	0.0252***			0.0533***	0.0551***			0.0009	-0.0050***
			(0.0016)	(0.0016)			(0.0017)	(0.0017)			(0.0015)	(0.0015)
HHI			0.1014***	0.1665***			-0.1957***	-0.0413***			0.2727***	0.2444***
			(0.0086)	(0.0098)			(0.0090)	(0.0102)			(0.0080)	(0.0091)
Usage of Stocks				0.1361***				0.1318***				0.1038***
				(0.0067)				(0.0070)				(0.0063)
Usage of Funds				0.1419***				0.2439***				0.0261***
				(0.0053)				(0.0055)				(0.0049)
Constant	0.5092***	0.0065	-0.2455***	-0.4699***	0.3513***	-0.0025	-0.4058***	-0.7807***	0.3489***	-0.1825***	-0.2481***	-0.2835***
	(0.0091)	(0.0091)	(0.0167)	(0.0183)	(0.0091)	(0.0097)	(0.0176)	(0.0191)	(0.0087)	(0.0085)	(0.0156)	(0.0171)
Observations	60,986	60,986	60,986	60,986	60,986	60,986	60,986	60,986	60,986	60,986	60,986	60,986
R-squared	0.0114	0.2102	0.2147	0.2337	0.0057	0.1045	0.1321	0.1661	0.0217	0.2591	0.2738	0.2906

Table A 2.2: Net portfolio performance controlling for inexperience

This table shows the results of a market model, in which two SFP specifications are separately regressed on the difference between the portfolio return and the risk-free rate (3-month euro Cash) on a daily basis. The "Full portfolio" specification includes all products. The specifications "LSFP contribution" indicates how the portfolio return alters if these products are included. The constant, which is annualized, displays the SFP contribution after excluding all investors with less than 24 months of investment experience. Robust p-values are in parentheses, and ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	Full portfolio	LSFP contribution	Full portfolio	LSFP contribution
Net return (no SFP)	0.895	0.995	0.892	0.991
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Constant (per annum)	-0.016	-0.016	-0.016	-0.016
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Observations	2,061,927	2,061,928	2,061,927	2,061,928
R-squared	0.737	0.809	0.738	0.811
Investor-fixed effect	NO	NO	YES	YES
Number of portfolio ID			27,578	27,578

Table A 2.3: Net portfolio performance controlling for overconfidence

This table shows the results of a market model, in which two SFP specifications are separately regressed on the difference between the portfolio return and the risk-free rate (3-month euro Cash) on a daily basis. The "Full portfolio" specification includes all products. The specifications "LSFP contribution" indicates how the portfolio return alters if these products are included. The constant, which is annualized, displays the SFP contribution after excluding the 25% of investors with the highest turnover. Robust p-values are in parentheses, and ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	Full portfolio	LSFP contribution	Full portfolio	LSFP contribution
Net return (no SFP)	0.992	1.021	0.991	1.019
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Constant (per annum)	-0.016	-0.014	-0.016	-0.014
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Observations	5,913,198	5,913,198	5,913,198	5,913,198
R-squared	0.874	0.892	0.874	0.892
Investor-fixed effect	NO	NO	YES	YES
Number of portfolio ID			42,153	42,153

Table A 2.4: Linear probability model with LSFP investor classifications as dependent variables

This table displays the results of a linear probability model, which tests the influence of personal and trading characteristics of sample investors on the probability to be classified into the three LSFP user groups. Columns 1 to 4 consider dynamic hedgers, columns 5 to 8 and columns 9 to 12 show the effects on being classified as hedger or speculator, respectively. Risk class is a variable by which investors indicate their risk tolerance with 5 being the least risk averse and HHI measures portfolio concentration, where higher numbers result in higher concentration and consequently less diversification. There are standard errors in parentheses and ***, **, * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	Dynamic Hedger				Hedger				Speculator			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Age	0.0029***	0.0029***	0.0017***	0.0018***	-0.0009***	-0.0009***	-0.0015***	-0.0014***	-0.0019***	-0.0020***	-0.0003	-0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Self-Employed	-0.0236***	-0.0206***	-0.0175**	-0.0158**	-0.0177**	-0.0173**	-0.0164**	-0.0158**	0.0413***	0.0379***	0.0339***	0.0316***
	(0.0080)	(0.0080)	(0.0079)	(0.0078)	(0.0069)	(0.0069)	(0.0070)	(0.0070)	(0.0075)	(0.0074)	(0.0071)	(0.0071)
Risk Class (min = 1, max = 5)		-0.0475***	-0.0455***	-0.0416***		-0.0076**	-0.0069**	-0.0061*		0.0551***	0.0524***	0.0477***
		(0.0036)	(0.0035)	(0.0035)		(0.0031)	(0.0031)	(0.0031)		(0.0034)	(0.0032)	(0.0032)
ln(Portfolio Value)			0.0354***	0.0379***			0.0174***	0.0174***			-0.0529***	-0.0553***
			(0.0030)	(0.0030)			(0.0027)	(0.0027)			(0.0027)	(0.0027)
HHI			-0.3061***	-0.2891***			-0.1260***	-0.1207***			0.4321***	0.4098***
			(0.0168)	(0.0168)			(0.0148)	(0.0149)			(0.0152)	(0.0152)
Usage of Stocks				0.0001				0.0540**				-0.0541**
				(0.0247)				(0.0219)				(0.0223)
Constant	0.2797***	0.4935***	0.2785***	0.2405***	0.2874***	0.3217***	0.2085***	0.1533***	0.4329***	0.1849***	0.5130***	0.6062***
	(0.0160)	(0.0227)	(0.0363)	(0.0419)	(0.0139)	(0.0198)	(0.0320)	(0.0371)	(0.0150)	(0.0212)	(0.0329)	(0.0379)
Observations	22,077	22,077	22,077	22,077	22,077	22,077	22,077	22,077	22,077	22,077	22,077	22,077
R-squared	0.0069	0.0147	0.0522	0.0587	0.0010	0.0013	0.0110	0.0118	0.0074	0.0194	0.1084	0.1202