Trading in Structured Products: Investor Behavior and Pricing Policies

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Abstract

For the last 10 years, we have witnessed a vast development of capital markets, introducing high frequency trading, bankruptcies of major institutions, and the establishment of a market designed for small investors. For a long period of time, retail investors have solely been able to invest in stocks, bonds, or funds. Today, structured products facilitate an advanced level of trading for retail investors allowing more sophisticated trading strategies and short term speculation.

In my work I focus on structured products offering numerous risk-return variations on a broad landscape of underlying assets. Compared to traditional investment opportunities, structured products are often considered a more complex level of investing, even allowing for betting on sideways and falling markets. However, within the last years, academics and regulators alike criticized the complexity of such products, hiding risks from investors. Due to the fact that structured retail products are issued as bearer bonds, liquidity, i.e. buy and sell prices, for such products are exclusively provided by the issuing investment bank. Yet, while investors are now more than ever capable of behaving like semi-professional traders, they could also be subject of exploitation by issuers. An important question is therefore whether investors put structured products to good use and whether issuers provide a fair and transparent environment.

This thesis studies both issuing investment banks and investors in the market for structured products. I analyze whether issuers exploit investor ignorance and whether investors benefit from this new market segment. My findings suggest that issuers use their exclusive position to increase their rents on the expense of retail investors. The degree of exploitation varies strongly between product types and issuers. Examining retail investor trades in short term speculation products reveals that investors do not perform well in general and have, on average, no informational advantage. (Non-)profitability is driven to a large extent by transaction costs. Analyzing retail investor trades with respect to the risk incurred reveals a poor investment on average. Investors expose themselves, i.e. their wealth, to great risk in order to realize potential profits.

Whether the regulator should step in to protect investors from losing money due to their own misplaced actions and, to a smaller extent, the service charge in form of hidden issuer fees remains beyond the scope of this thesis. Altogether, the findings of this thesis suggest that regulators should pay close attention to the behavior of participants in the market for structured products.

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Chapter 1

Introduction

"So, over the years we have often seen product design, marketing and sales processes accentuate and distort the effects of human biases: teaser rates to take advantage of customer inertia; bizarre insurance exclusions tucked away in the small print; terms and conditions for financial products longer than Hamlet."

Martin Wheatley (Chief Executive of the Financial Conduct Authority)

1.1 Motivation

ENGAGING in financial transactions is strongly linked to joy, regret, prosperity, and social insecurity. No matter whether buying insurance, closing up a mortgage, or investing in financial markets — to avoid poor decisions, consumers either have to be very well informed and rational, or they put trust in their advisors. On September 15, 2008 between 40,000 and 50,000 German investors lost more than EUR 700 million due to underestimation and ignorance of existing risks.[1] On

[1]Source: http://www.ftd.de/unternehmen/finanzdienstleister/:grundsatzurteil-lehman-anleger-bekommen-kein-geld-zurueck/60109511.html. Accessed 07/06/2013. Numbers are only estimations by several German institutes. An older article from the NY Times quotes losses of ca. EUR 500 million for 60,000 investors: http://www.nytimes.com/2008/10/15/business/worldbusiness/15lehman.html?_r=0. Accessed 07/06/2013.

that day Lehman Brothers filed for bankruptcy.[2] Lehman Brothers was an issuer of structured products that were distributed by, among others, German banks such as private banks, cooperative or savings banks. Structured (retail) products are bearer bonds, which become worthless in case of a default of the issuer (default risk). They are specifically designed to cater for the needs of retail investors. Investors with less capital at hand, no access to derivatives, and limited knowledge of financial markets (see, e.g., Ruf, 2011; Das, 2001). Structured products grant investors access to sophisticated trading strategies and risk-return profiles for a broad range of different market expectations. Although, the default risk is outlined in product descriptions, investors were often not fully aware of it. Some relied blindly on their bank advisors and many others did not comprehend the magnitude and probability of all involved risks.[3] Various advised investors sued their banks on the basis of wrong consultation.[4]

Put simply, structured products are a well marketed cloak for the combination of several financial securities, such as bonds and derivatives written on commodities, currencies, indices, single or multiple stocks. This *structuring* of financial products in form of bearer bonds leads to a distinct difference compared to regular stocks regarding the price discovery. Prices for stocks are usually determined through the limit order book at an exchange, consisting of orders of investors willing to buy or sell for their submitted price (see, e.g., Harris, 2003). However, in case of structured products issuers are in the exclusive position to set buy and sell prices for their own products without any direct price competition. Investors cannot go short in a product. Thus, the market design does not lead to efficient prices by its own. Consequently, issuers are in a quasi-monopolistic position (Grünbichler and Wohlwend, 2005).

Among the most popular product types are *bonus certificates*. With bonus certificates investors participate in the underlying asset and are protected from losses up to some extent. At the end of the life time investors receive a bonus payment if a predefined lower threshold of the underlying asset has not been touched. Bonus certificates incorporate a barrier option. Barrier options start or cease to exist when the

[2] Official press release: `http://www.lehman.com/press/pdf_2008/091508_lbhi_chapter11_announce.pdf`. Accessed 06/23/2013.

[3] See, for example, `http://www.sueddeutsche.de/geld/anleger-und-die-lehman-pleite-geplatzte-traeume-1.691296`. Accessed 08/20/2013.

[4] See, for example, `http://www.welt.de/print/welt_kompakt/print_wirtschaft/article108749826/Ehepaar-erstreitet-nach-Lehman-Pleite-7-4-Millionen.html`. Accessed 07/08/2013.

underlying touches a predefined level. Although, the functionality is easy to understand, the comprehension of an acceptable price is not. It requires experience with asset pricing models, available data on the option market and the underlying market, as well as the expertise to combine everything into a final price. Therefore, it seems impossible for retail investors to actually look behind the marketing wall and decide on a well-informed basis whether a product is fairly priced (Bethel and Ferrel, 2007). Despite this lack of knowledge, German retail investors generate a total turnover of about EUR 100 billion per year in structured products.[5] Although, the bankruptcy of Lehman Brothers represents a major setback for many investors, the German market for structured products is still the most advanced and sophisticated market designed for retail investors worldwide. From 2008 to 2013, the product universe has risen from approximately 200,000 tradable products to more than one million products. Retail investors can trade at low costs on all imaginable market movements and expectations. Every retail investor is able to act like a (semi-) professional trader and can take an active part in his own investment strategies. Before the introduction of this market segment, investors could solely buy funds, bonds, or stocks, which only allowed for a limited playground of financial strategies.

However, new services and opportunities always come at a price. Due to the enormous complexity of those products and the easy access to trading them, ordinary retail investors are not capable of identifying whether the price of a product is accurate and fair. This allows for fuzzy pricing strategies by issuers, which might aim to exploit retail investors' ignorance (Carlin, 2009; Carlin and Manso, 2010). Similar to insurance contracts, where one usually does not know how much of the money is spent on fees and premium for the sales person, retail investors have to think carefully whether costs and risks are acceptable.

Martin Wheatley is the head of the Financial Conduct Authority (FCA), a new regulator in the UK that was formed in 2013 as a consequence of the last financial crisis, aiming for a better protection of investors. Wheatley argues for a new era of regulation taking into account behavioral biases of investors:

> *"You have to assume you don't have rational consumers. Faced with complex decisions or too much information, they default... They hide behind credit ratings*

[5]See Section 2.3 for more information.

agencies or behind the promises that are given to them by the salesperson."[6]

The market for structured products facilitates every strategy an investor can imagine. However, if this results in gambling and poor investment decisions it is up to the regulator to weigh opportunities and potential misuse of this market. Hens and Rieger (2011) point out that the utility gain of structured products compared to the classic approach of combining a risky asset (investing in the underlying) and a risk-free investment is negligible even given considerably low costs. They argue that behavioral characteristics such as irrationality, loss-aversion, and misjudgment of probabilities are likely explanations for the attractiveness of this market. The under-estimation of probabilities is further supported by Rieger (2012) based on survey results. Based on a survey of 757 German investors, Fischer (2007) finds that, besides diversification and hedging of portfolios, gambling is a frequent motive for trading in structured products. In addition, he finds that investors act irrationally, often failing at a proper diversification or hedging strategy. Moreover, irrationality seems to increase with a higher risk tolerance.

From a regulators' perspective, this raises the question whether investors should have the easy possibility to trade products they do not understand, and whether you should regulate against all to protect some from being victimized? John Cochrane, a renowned economist, thinks differently:

> *"Protecting" people because the bureaucracy just thinks it knows how to run people's lives better than they do. This used to be called aristocratic paternalism. Now it's defended by a misreading of behavioral economics.*[7]

This thesis provides insights into the behavior of both issuers and investors in this market, identifying possible exploitation by issuers and analyzing trading decisions by investors. Combining both results provides a fundamental ground for future regulation.

[6] `http://www.fca.org.uk/news/speeches/human-face-of-regulation`. Accessed 07/06/2013.

[7] `http://johnhcochrane.blogspot.ca/2012/01/consumer-financial-protection-1984.html`. Accessed 07/08/2013.

1.2 Research Outline

This thesis aims to explore characteristics and behavior of both issuers and investors as well as their interaction in the German market for structured products. Issuers have imposed upon themselves the obligation to set fair prices for their products (Deutscher Derivate Verband, 2007). However, the last years have shown that investors and regulators alike become increasingly skeptical towards the intransparent situation.[8] Issuers do not provide any information on hidden fees, incorporated in their products, as well as on their influencing factors (see, e.g., Bethel and Ferrel, 2007). Thus, investors have to belief that overall competition across similar existing products and regulatory initiatives prevent them from being exploited.

Specifically, research contained in the work at hand is broken down into two major research topics, addressing transparency and benefits of this market. Generally, in markets that do not provide fully transparent information, investors may be subject to exploitation by the market system and/or its dominating participants. However, providing all (relevant) information is usually impossible. Thus, this dilemma raises the question of the ideal level of information provision. The first research question addresses this problem of (missing) transparency and, thus, the potential extent of exploitation in the market for structured products:

Research Question 1. *Do issuers exploit the ignorance of retail investors?*

To shed light on this matter, I examine differences between theoretical prices, derived from a standard asset pricing model and quoted issuer prices for several popular product types. In the following, this difference is called premium or margin and gives, in this raw form, an indication for the level of exploitation (Wilkens et al., 2003; Wilkens and Stoimenov, 2007; Baule, 2011). I run a two-fold approach to detect possible influencing factors on the included premium. First, I analyze whether issuers systematically adjust their premiums during the day and over the life of a structured product. Usually, structured products have a finite life time ranging from a few months to several years. Continuously decreasing premiums result on aver-

[8] For example, the board of the International Organization of Securities Commissions (IOSCO) published in April 2013 a consultation paper which supports the discussion about the disclosure of hidden fees and fair values of structured products. See `http://www.iosco.org/library/pubdocs/pdf/IOSCOPD410.pdf`. Accessed 06/26/2013.

age in higher buy prices and lower sell prices and, thus, support the assumption of investor exploitation, as will be discussed in more detail in later chapters. Second, based on retail investor trading data, I analyze whether issuers deliberately anticipate retail investor behavior to increase their profits.

Independent from hidden costs or possible unknown exploitation approaches by issuers, it is still to be discussed whether retail investors make good use of this market structure and resulting sophisticated trading strategies. This new market regime allows, in contrast to traditional investing, to trade on a (semi-) professional level. Traditionally, retail investments have been focused on retirement portfolios and thus long-term investments. Retail investors bought funds, stocks, and bonds aiming for a higher average long-term profit compared to risk-free assets. Today, retail investors can enter positions for only minutes and exit with huge profits, something alike has never been possible this easy before. This leads to the second overall research question, focusing on this market from the perspective of overall economic benefit for retail investors:

> **Research Question 2.** *Is trading in structured products beneficial for retail investors' wealth?*

In recent years a major part of trading volume in the German market for structured products has been generated in leverage products, i.e. products that participate disproportionately in the underlying asset. Leverage products are not suitable for long holding periods, but for speculation in the short term (Entrop et al., 2011). So far it is unknown whether retail investors use this new opportunity to incorporate private information in the market or if they merely trade for sensation seeking and entertainment. Studies such as Dorn et al. (2012) show that some groups of investors tend to substitute gambling with trading lottery-like stocks.

Altogether, the above research questions aim to provide a comprehensive picture of all participating parties in this innovative market, providing in-depth analyses of both, issuers and investors with respect to the regulatory environment.

1.3 Structure of the Thesis

The remainder of this thesis is organized as follows. Chapter 2 provides a solid background on the market for structured products in Germany, including a description of the market design, the most popular product types, market statistics for several European countries, and an overview of the current regulatory environment. Chapter 3 provides a literature overview regarding the behavior of market participants, i.e. issuers and investors. The first part summarizes empirical and theoretical studies focusing on the pricing of structured products in Germany and other comparable markets. Second, literature regarding retail investor trading and its outcomes on performance and order aggressiveness are presented. Additionally, I present well-known decision-making failures and behavioral biases, which are relevant for this thesis. The subsequent chapter presents information on used data sources as well as a detailed description and discussion of limitations of the methodological approach used to derive prices for structured products. Chapter 5 analyzes the price-setting behavior of German issuers with respect to several influencing parameters and its effect on retail investor wealth.[9] Chapter 6 examines retail investor behavior, focusing on leverage structured products.[10] It aims to study how well informed retail investors are from different perspectives. Chapter 7 summarizes the key contributions of this thesis, discusses regulatory implications, and outlines promising related topics for future research.

[9] Parts of this chapter are joint work with Felix Fritz (Fritz and Meyer, 2012) and have been presented at the 20th Finance Forum (Oviedo, Spain) and the Stuttgart Stock Exchange Research Colloquium 2012 (Stuttgart, Germany). It has been invited for presentation at the 25th Australasian Finance & Banking Conference (Sydney, Australia), the 2012 Auckland Finance Meeting (Auckland, New Zealand), the International Mathematical Finance Conference (Miami, USA), and the 49th Annual Meeting of the Eastern Finance Association (St. Pete Beach, United States). Some parts of this chapter are based on a joint working paper with Ryan Riordan (Meyer and Riordan, 2013). Additionally, an overview article based on some of the results contained in this chapter has been published (Meyer et al., 2013).

[10] This chapter is based on a joint paper with my colleagues Sebastian Schroff and Christof Weinhardt (Meyer et al., 2013). A previous version was circulated under the title "Lottery Losses of Retail Investors". Results have been presented at the 22nd European Financial Management Association (EFMA) conference (Reading, UK) and at the 30th International French Finance Association Conference (AFFI) (Lyon, France). The paper is forthcoming in *Financial Markets and Portfolio Management*.

Chapter 2

The Universe of Structured Products

THIS chapter provides a solid background on characteristics of structured products and the regulatory environment. Taken together, it builds the foundation for all upcoming analyses that particularly focus on the German market for structured products, which is among the most advanced markets worldwide. I describe the German market structure, focusing on design aspects of tradable securities (Section 2.1) and of the market itself (Section 2.2). Section 2.3 provides details on popular product types with respect to their risk and investor target group as well as descriptive statistics for both, the German and other European markets. Section 2.4 presents information on regulatory aspects for the German market as well as its differences to other European markets with respect to listing fees.

2.1 Product Design

A structured retail product is a bearer bond issued by an investment bank.[1] Similar expressions are bank-issued product or securitized derivative. Although, there is no uniform definition of a structured product across exchanges or countries, they have a basic feature in common: they are all built through a combination of fundamental financial securities, such as derivatives, equities, indices, bonds, currencies,

[1]A bearer bond is a "bond not registered in the name of an owner and that therefore belongs to whoever holds the bearer certificate. Dividends or interest payments are claimed using coupons attached to the certificate, which is transferable and negotiable without endorsement." (Financial Times Lexicon, `http://lexicon.ft.com/Term?term=bearer-stock/bond`. Accessed 08/07/2013.)

or commodities. The Federation of European Securities Exchanges (FESE) defines a structured product as a "tradable financial instrument designed to meet specific investor needs and to respond to different investment strategies, by incorporating special, non-standard features."[2] The payoff at maturity, i.e. at the end of the life time of the product, is defined through exact formulas published by issuers. Although, such formulas are based mainly on the performance of the underlying asset, several more exotic conditions are sometimes included. This includes conditions and features such as lookback, dual currency, ranges, targets, moving barriers, accrual, podium, or cap. Each of them increases the complexity of the structured product and the return formula. Thus, the payoff profile gives the impression of a 'constructed' return.

Structured products fill the gap for investors with partly insufficient funds, knowledge, and access possibilities to create such complex security combinations themselves. Therefore, primary customers for structured products are retail investors (Bethel and Ferrel, 2007). Besides not having the expertise to combine fundamental financial securities to a more complex product in a successful manner, a reason for retail investors to invest into a structured product, instead of a direct investment in the underlying basic components, is the reduced transaction costs. For example, investing in products with an index as underlying is cheaper than manually duplicating the index by buying all constituents. Additionally, share prices of structured products are reduced to an investor friendly level, which allows for small investments. This is achieved by introducing a subscription ratio. For example, a subscription ratio of 1:10 for a structured product means that investors participate to the tenth of the return of the underlying asset. In volume terms, assume the price of the structured product to be EUR 10 with a subscription ratio of 1:10, and the underlying asset price to be EUR 100. If the price of the underlying increases by EUR 10 the price of the structured product increases by EUR 1.

To achieve payoff profiles similar to structured products, investors have to be able to trade derivatives. However, retail investors usually have no access to option exchanges through their broker. Therefore, structured products allow for sophisticated trading strategies and provide a relatively new investment opportunity besides tradi-

[2]This quote is taken from the FESE methodology which can be found at: `http://www.fese.be/_lib/files/FESE_Statistics-Methodology_5_2_January10_FINAL.pdf`. Accessed 05/10/2013.

tional investments in stocks, funds, or bonds. With the possibility to indirectly enter a short position in an underlying, structured products can serve as a hedging instrument for retail investor portfolios. A wide range of product characteristics allows investors to find a product, which perfectly matches their risk-return profile. Structured products are issued in a variety of different combinations and maturities. In case of a stock as underlying, the investor has no rights (e.g., voting rights) whatsoever regarding the underlying and usually has to forego occurring dividend payments. Issuers withhold dividend payments and often adapt product prices to the expectation of future dividend payments.

Due to the legal structure of structured products, it is not subject of any deposit protection. Therefore, invested money bears the risk of a total loss in case of a bankruptcy of the issuing investment bank. In 2008, this case became true with the collapse of Lehman Brothers.[3]

2.2 Market Design and Trading Possibilities

In Germany, structured products can be traded in two ways. First, via an over-the-counter (OTC) platform of a bank or broker and, second, via market segments of regulated exchanges such as Scoach[4] in Frankfurt or EUWAX in Stuttgart. Retail investors do not need a trading license or proof of specific knowledge to trade structured products. Nevertheless, regulation requires companies to enquire information about the securities-related knowledge, experience, investment strategy, and financial background of customers to recommend suitable financial instruments. Therefore, investors have to provide information regarding their investment skills upon registration with their broker. This survey is designed in a simple manner, often limited to the question whether they have already traded different security groups. In addition, investors are required to confirm that they are aware of the risks involved before they are allowed to submit an order with their broker. There is no additional

[3]Source: e.g., http://www.nytimes.com/2008/10/15/business/worldbusiness/15lehman.html?_r=0. Accessed 07/06/2013.

[4]In November 2013 Deutsche Boerse and SIX have started to go separate ways regarding their joint structured products exchange Scoach. It is now simply known as Boerse Frankfurt. I consequently use Scoach as name for this exchange throughout this thesis since it has been this way during all sample periods used in this thesis.

human supervision that might interfere with the answers of such surveys. As a result, any investor can trade any retail product as long as he fills out the survey correctly. Martin Wheatley outlines this procedure in the following way[5]:

> *"They were required to tick boxes, that they had high risk appetites, that they read and understood the terms and conditions. That is always a joke, but that's what people tick. That it was their own decision."*

In 2013, more than one million different structured products are tradable in Germany.[6] Liquidity cannot be provided by investors themselves. To ensure that investors are able to trade each structured product at any given time market makers are needed. The issuing investment banks assume this role for their own products. Issuers provide quotes for their products continuously throughout the day which are binding for a predefined order volume.[7] Therefore, investors (almost) always trade against the issuing bank, i.e., against the best ask or best bid offered by the issuer. Nevertheless, it is possible that orders are executed within the spread of the issuing investment bank due to the matching with another order. However, this happens only very scarcely due to the huge number of tradable products. Although it is possible to enter long or short positions on an underlying through an investment in structured products, it is not possible to enter a short position in a product. As a consequence, investors always have a long position (the put or call product) in their portfolio and thus losses are limited to the amount of money originally invested. The two regulated market segments in Germany, Scoach and EUWAX, have a slightly different market

[5]The quote is an excerpt of the speech given by Martin Wheatley at the Lansons Future of Financial Services Conference 2013. Source: `http://futureoffinancialservices.co.uk/conference-materials/`. Accessed 09/26/2013.

[6]See Section 2.3 for market statistics.

[7]Scoach: "In the case of investment products, this minimum quoted volume is EUR 10,000 or 10,000 units. In the case of leveraged products, it is EUR 3,000 or 3,000 units. Usually, significantly larger orders are executed at the current bid and asked prices." (Quotation taken from `http://www.scoach.de/en/about-us/scoach-europa/trading`. Accessed 06/23/2013.).
EUWAX: "The trading volume, for which a bid and offer price quoted by a market maker has a minimum validity (minimum quotation volume), must amount to at least Euro 3,000 for securities quoted per unit (leverage products) and Euro 10,000 (investment products) or Euro 10,000 per security. A nominal amount of at least Euro 10,000 must be made available for securities listed in percentage terms. Trading restrictions are put in place in the event that there are technical problems with regard to the availability of market maker quotes." (Quotation taken from `https://www.boerse-stuttgart.de/en/tradingsegmentsandtradinginitiatives/euwax/trading.html`. Accessed 06/23/2013.).

structure. Orders sent to Scoach are processed fully electronically and are, in case of a market order, matched automatically against binding quotes of the issuing investment banks. In contrast, Stuttgart Stock Exchange employs additional human market makers besides their electronic trading system. A market maker can step in between investment banks and investors in times of high uncertainty or is able to provide an execution price which is slightly better than the current best bid or best ask provided by the issuer. Additionally, market makers at Stuttgart Stock Exchange are included into the order execution process if deviations between quoted prices are substantially higher than expected.

Trading hours at exchanges are from 08:00 a.m. until 08:00 p.m., whereas in OTC markets orders are often executed until 10:00 p.m.Outside trading hours of a product's underlying, indications are often used to derive prices. For example, after the final daily DAX closing price at 5:30 p.m. Deutsche Bank or Lang & Schwarz still update their indications until 10:00 p.m.

2.3 Product Universe

Germany is the most advanced country in terms of retail investment products, offering more than one million products in 2013. Structured products can be divided into two distinct groups: (i) investment products and (ii) leverage products. Investment products are designed for long-term investments with a rather conservative risk-return profile. Leverage products can be used either as short-term speculation instruments or to hedge investor portfolios.[8]

Market Statistics

Germany All statistical data for this section is retrieved from the German Derivatives Association (DDV).[9] Figure 2.1 shows the development of the monthly outstanding volume in the German market of structured products. From start to end for the period ranging from 2005 to 2013, an increase of EUR 40 billion, with an out-

[8] For a more detailed overview of different product types in Germany see Table B.1 in the appendix.
[9] `http://www.derivateverband.de/ENG/Home`. Accessed 09/20/2013.

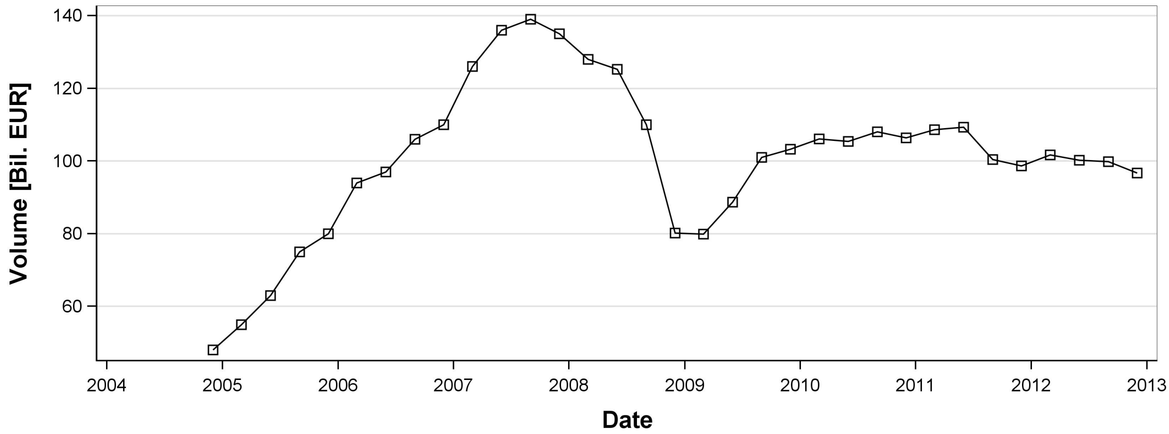

FIGURE 2.1: **German Structured Products Monthly Outstanding Volume.** This figure shows the development of monthly outstanding volume for the German market of structured products, starting from December 2004.

standing volume of currently nearly EUR 100 billion per year. The huge drop in outstanding volume towards the end of 2008 might be driven by investors' loss of trust in structured products due to the bankruptcy of Lehman Brothers. The number of tradable products has been growing continuously for the last years as presented in Figure 2.2. Unfortunately, monthly issuance data from DDV is not available prior December 2007. The number of tradable products increased by approximately 400% from roughly 250,000 products in 2008 to more than one million products in 2013 issued by 16 companies. Among all issuers, Commerzbank and Deutsche Bank have the highest market share (outstanding volume) with 15.9% and 16.5%, respectively.[10] Investment banks issue relatively more products towards the end of each quarter, which is possibly driven by maturity dates of EUREX options, which are a basic component of most products. The strong increase of the number of tradable products within the last years has been certainly made possible through faster and more efficient IT systems at investment banks and exchanges. Since products have to be quoted continuously, IT systems have to withstand huge traffic loads during peak trading.

[10]DDV data as of June 2013: `http://www.derivateverband.de/DE/MediaLibrary/Document/PM/13%2008%2016%20PM%20Marktanteile,%20Juni%202013.pdf`. Accessed 09/20/2013.

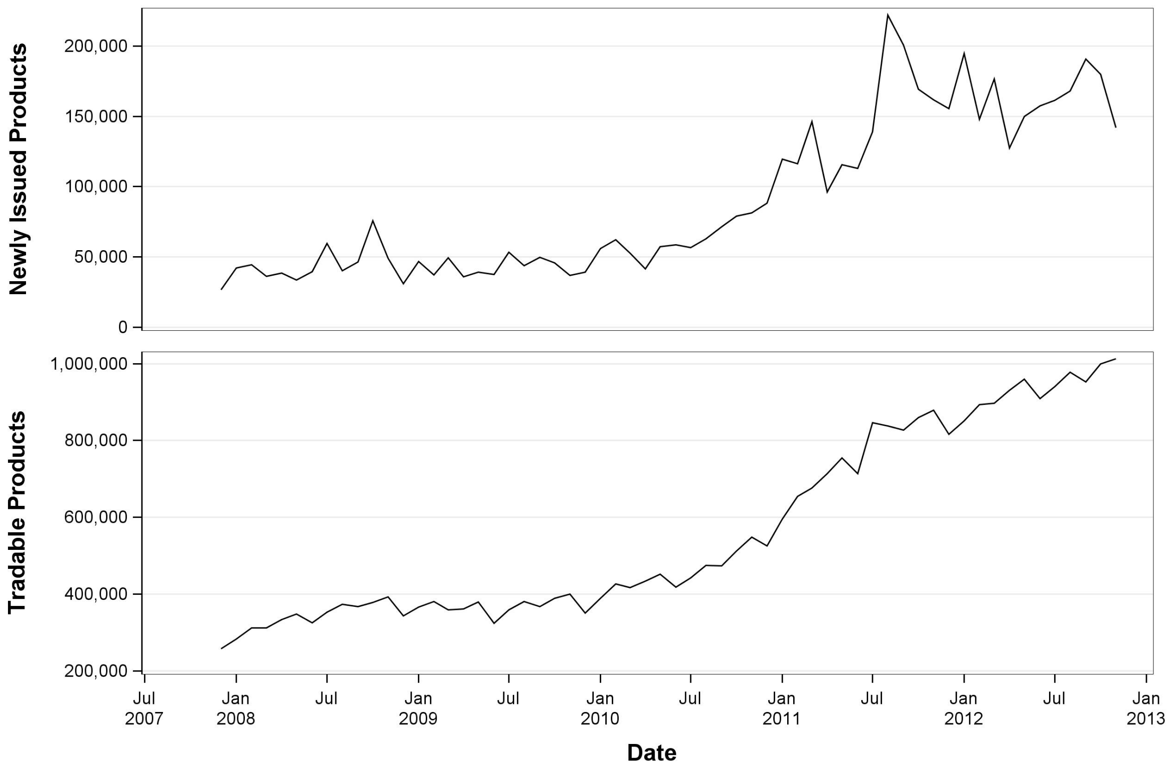

FIGURE 2.2: **Issuance Development in Germany.** The upper figure shows the number of newly issued structured products per month across all issuers. The lower figure visualizes the total number of tradable products.

Europe The European Structured Investment Products Association (EUSIPA) provides descriptive statistics about the European market starting from the second quarter in 2011.[11] Figure 2.3 shows the number of tradable structured products in Europe, i.e., Austria, France, Italy, Sweden, Switzerland, and Germany. The number of listed leverage products has exceeded the number of investment products for the observation period, ranging from the second quarter of 2011 until the second quarter of 2012. As for the German market, this pattern is still observable in 2013. At first sight, it is

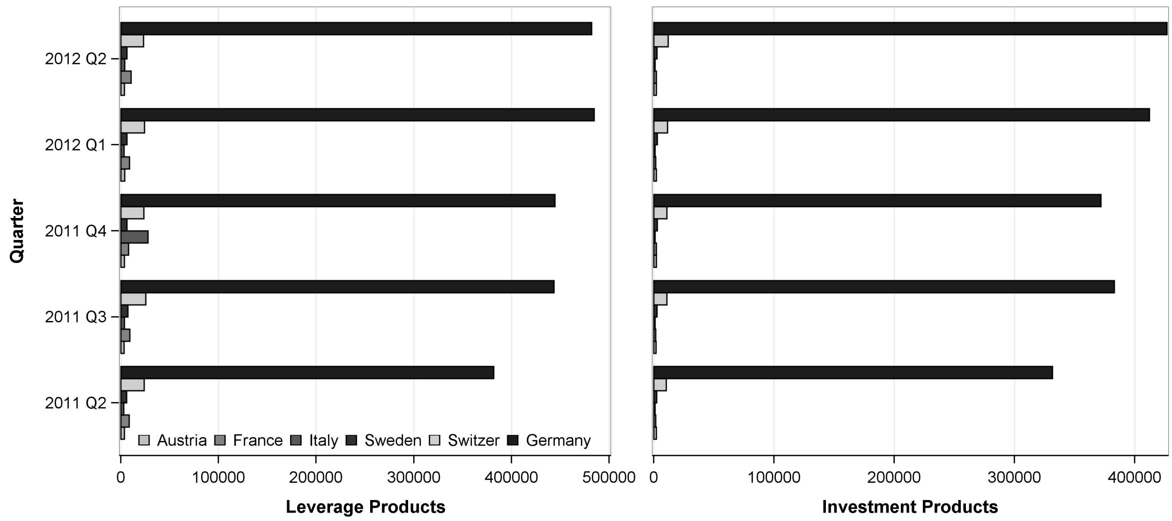

FIGURE 2.3: **Listings of Structured Products in Europe.** This figure shows the number of tradable structured products in Europe grouped by countries and distinguished by overall product type (left: leverage products; right: investment products).

obvious that the German market of structured products is more developed compared to other European markets. Its number of listed products is roughly hundred times the number of foreign markets. German investors face a greater product variety compared to their European neighbors. The substantial growth in the number of products in Germany is at least to some extent due to the lower listing fees that are discussed in detail in Section 2.4. Figure 2.4 visualizes quarterly turnover grouped by country and overall product group. I observe that German and Swiss investors generate the highest turnover in Europe. This effect is more pronounced for investment products compared to leverage products.

[11] EUSIPA data is accessed through the German Derivatives Association: `http://www.derivateverband.de/DEU/Politik/Europa/Marktstatistiken`. Accessed 07/01/2013.

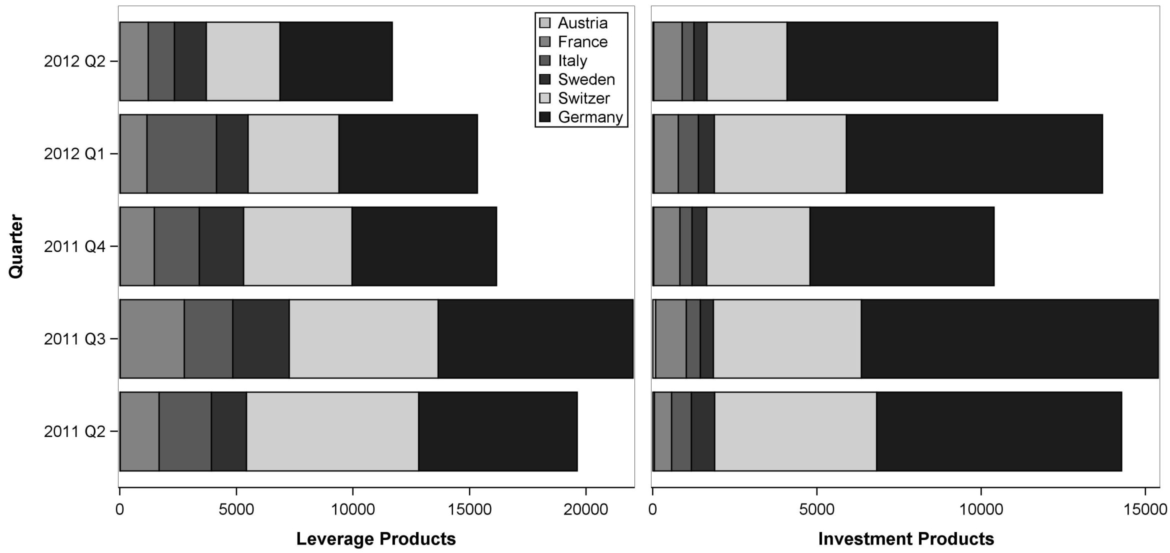

FIGURE 2.4: **Turnover of Structured Products in Europe.** This figure shows the total reported turnover of structured products in Europe grouped by countries and distinguished by overall product type (left: leverage products; right: investment products).

Investment and leverage products are designed for different market expectations and risk appetites of investors. In the following, I present the most popular German product types that have been analyzed in this thesis.

Investment Products

Discount Certificate Discount certificates are the most popular investment product type in Germany. In August 2013, 19.3% of the total turnover was generated in discount certificates.[12] It offers investors the possibility to invest in the underlying asset with a discount. However, the maximum payoff is capped. Depending on the difference between current underlying price and the cap of discount certificates, different risk-return expectations can be met. Figure 2.5 shows the payoff diagram of a discount certificate. As long as the underlying does not raise above the cap level, the investor has a higher return compared to a direct investment in the underlying. The additional discount on the underlying price results in a small protection from occurring losses in the underlying. If the price at maturity is higher than the cap level the

[12] See DDV August 2013 statistic: `http://www.derivateverband.de/DE/MediaLibrary/Document/PM/08%20B%C3%B6rsenumsatzstatistik%20August%202013.pdf`. Accessed 09/23/2013.

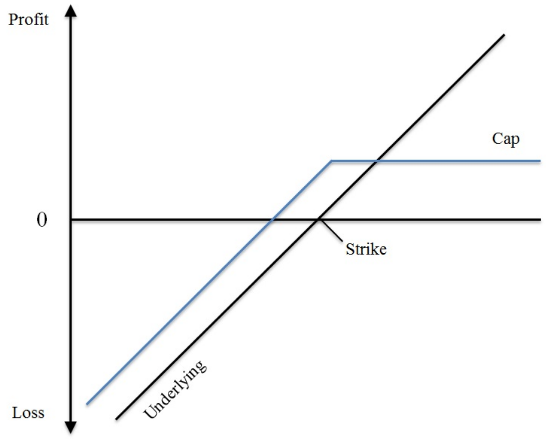

FIGURE 2.5: **Payoff: Discount Certificate.**

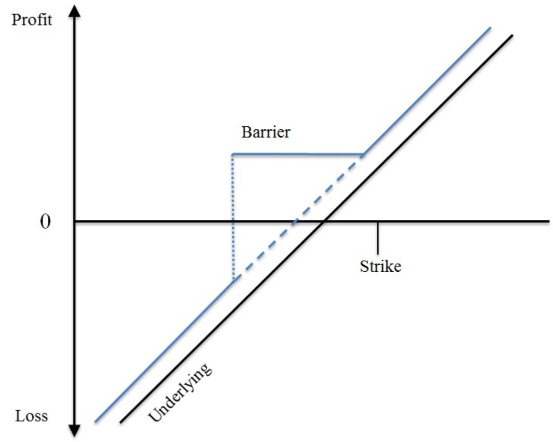

FIGURE 2.6: **Payoff: Bonus Certificate.**

investor only receives the amount of the cap level as payoff. Discount certificates are designed for investors who expect the underlying to be slightly rising or sideways trending. It can be constructed through the combination of a zero-strike call and the sale of a call option.[13]

Bonus Certificate A (classic) bonus certificate is a participation product which is designed for a sideways trending or slightly rising underlying similar to discount certificates. If the underlying never touched a predefined lower barrier the investor obtains a bonus payment at maturity. This bonus payment is achieved through the abandonment of dividend payments by the investor. Bonus certificates are more conservative compared to discount certificates due to the additional bonus payment which offers a better protection against losses of the underlying. Figure 2.6 shows the payoff diagram of a bonus certificate. If the barrier has been hit the bonus dissolves and the investor participates linearly from the underlying. In other words, the bonus certificate becomes a regular tracker certificate. A tracker certificate has an identical payoff profile as the underlying asset. Ignoring dividend payments, it is therefore similar to a direct investment in the underlying asset. Tracker certificates are popular for underlying assets that are not suitable for a direct investment, such as indices.

[13] A different possibility to duplicate the payoff is to buy the underlying stock instead of a zero-strike call. This is also called covered call.

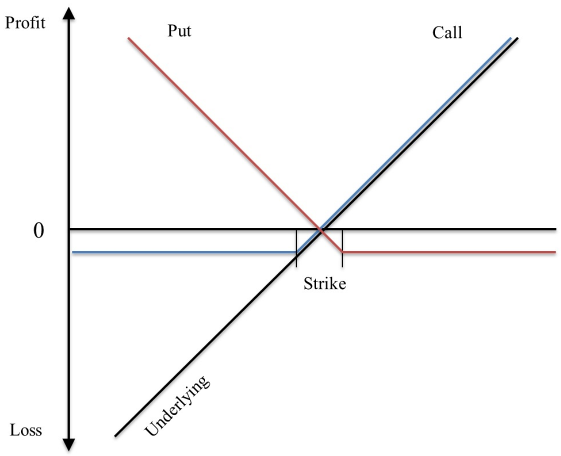

FIGURE 2.7: **Payoff: Warrant.**

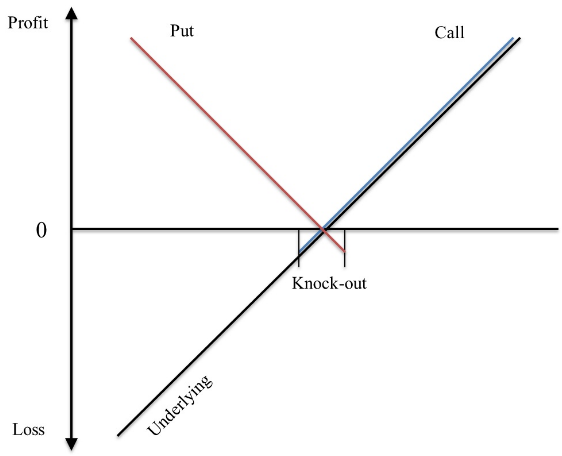

FIGURE 2.8: **Payoff: Knock-out Warrant.**

In only slightly rising markets, investors could achieve higher returns trading bonus certificates compared to a direct investment in the underlying. From a financial engineering perspective, a bonus certificate is built by combining a zero-strike call and a down-and-out put option. Besides classic bonus certificates, several variations exist. These include capped payoffs, multiple barriers, leveraged participation, and reverse products.

Leverage Products

Warrant Warrants are plain vanilla options issued by an investment bank. Issuers provide call as well as put warrants. Put warrants may be used by retail investors to hedge their portfolio against unexpected drops of their long positions. The payoff diagram at maturity is shown in Figure 2.7. The price of a warrant can be broken down into its intrinsic value and its time value. The time value is the additional expense an investor would pay for the probability that the underlying asset will move in the desired direction before the expiration date of the warrant. Consequently, the time value decreases with reduced time to maturity.

Knock-out Warrant Knock-out warrants resemble the payoff profile of classic warrants. However, knock-out warrants include an additional barrier which results in an immediate total loss if hit during the life of the product. Therefore, knock-out warrants are more risky securities compared to all other discussed product types. Figure 2.8 visualizes the payoff profile of call and put knock-out warrants. However, the payoff diagram does not reflect the major contribution of this product type from the investor's perspective. Depending on the moneyness level at which investors trade a knock-out warrant it magnifies price movements in the underlying to a much greater extent than (classic) warrants. As a result, this product type is primarily designed for very short holding periods and requires continuous monitoring. Behind the pricing scheme of a call (put) product of issuing investment banks is a down-and-out call (up-and-out put) barrier option.

2.4 Regulation and Listing Fees

> *The 'best and the brightest' at our top investment banks have expended great energy designing ludicrously complex financial products, which you need a Nobel Prize in physics to understand. Many investors were blind to the risks involved, equated complexity with security and were engaged in a bout of collective madness. Unfortunately you cannot regulate against stupidity.*
>
> - John McFall (Chairman of the UK Treasury Committee)

McFall summarizes that current regulation lacks to provide an environment of a transparent and understandable market.[14] The market of structured products is regulated through several institutions, national and international laws. Overall, regulation can be split into three major groups: (i) German law, (ii) European law, and (iii) corporate responsibility. Table 2.1 briefly shows applied laws distinguished by those groups.

German Law

The trading process evolves through several stages, starting from information aggregation and ending with order execution and post trade services (see for example Harris, 2003). German law protects investors in all of these stages. The German Civil

[14] Citation taken from press release available at `http://www.parliament.uk/business/committees/committees-archive/treasury-committee/tc0708pn30/`. Accessed 03/14/2013.

TABLE 2.1: **National and International Regulation.** This table shows an excerpt of laws which are applied to the German market of structured products.

Regulation	Paragraph	Title/Description
German Law		
German Civil Code (BGB)	§793 BGB	Rights under a bearer bond
	§794 BGB	Liability of the issuer
	§796 BGB	Objections of the issuer
	§799 BGB	Declaration of invalidity
	§801 BGB	Extinction; limitation
	§803 BGB	Interest coupons
Debenture Bond Act (SchVG)	§3 SchVG	Transparency of the promise to perform
Securities Prospectus Act (WpPG)		Requirements for product prospectuses
Securities Trading Act (WpHG)	§31 WpHG	Liability to provide information in an understandable manner
	§33a WpHG	Best Execution of Customer Orders
Regulation for Specifying Rules of Conduct and Organization Requirements for Securities-related Services Enterprises (WpDVerOV)		Issuer duties towards customers
Stock Exchange Act (BörsG)		Information on trading process and price fixing
European Law		
Prospectus Directive (Directive 2010/73/EU)		Requirements for product prospectuses
Packaged Retail Investment Products (PRIPs) (Proposal)		Transparency of retail investment products
MiFID (Directive 2004/39/EC, Directive 2006/73/EC)		Investor protection and exchange competition
Corporate Responsibility		
Derivatives Code		Definition of guidlines for trading and issuance of structured products

Code (BGB)[15] formally defines the right of a holder of a bearer bond to "demand from [the issuer] the act of performance in accordance with the promise [...]".[16] Additional articles regulate the liability (§794 BGB) and objections (§796 BGB) of the issuer, the declaration of invalidity of the bearer bond (§799 BGB), and its extinction (§801 BGB). Besides the formal definition in the German Civil Code, the Debenture Bond Act (SchVG)[17] states that "the terms and conditions of the notes must enable an investor who is well-informed with respect to the relevant type of notes to identify the performance promised by the issuer."[18] The Securities Prospectus Act (WpPG)[19] defines a set of additional transparency rules for the mandatory prospectus of a bearer bond. Issuers have to provide a binding prospectus for each bearer bond, which has to be approved by the German Financial Supervisory Authority (BaFin)[20]. Among other things, issuer have to clarify in such prospectuses the risk of a total loss through bankruptcy of the issuing investment bank. The WpPG is the national implementation of the European Prospectus Directive (Directive 2010/73/EU). Formally correct prospectuses are usually documents with up to 100 pages, which makes it highly unlikely that retail investors read all those information. The Regulation for Specifying Rules of Conduct and Organization Requirements for Securities-related Services Enterprises (WpDVerOV)[21] adapted to this situation by the formalization of the duty to provide an information sheet of no more than three pages which contains important facts of the product type. Providing information sheets for all different product types shall enable investors to take a well-informed decision on their own, without being dependent on bank representatives. Besides potential risks and functionality of the described product type, information sheets also have to provide revenue details for different market situations.

[15]German designation: Bürgerliches Gesetzbuch.

[16]Source: BGB Article 793 paragraph 1. English translation quoted from: `http://www.gesetze-im-internet.de/englisch_bgb/englisch_bgb.html#p3241`. Accessed 03/08/2013.

[17]German designation: Schuldverschreibungsgesetz.

[18]Source: SchVG Article 3. English translation quoted from `http://www.true-sale-international.de/fileadmin/tsi_downloads/Unternehmen/TSI_Partner/SchVG_2_spaltig_deutscher_Disclaimer.pdf`. Accessed on 03/13/2013.

[19]German designation: Wertpapierprospektgesetz.

[20]German translation: Bundesanstalt für Finanzdienstleistungsaufsicht.

[21]German designation: Verordnung zur Konkretisierung der Verhaltensregeln und Organisationsanforderungen für Wertpapierdienstleistungsunternehmen.

The Securities Trading Act (WpHG)[22] obliges securities-related services enterprises to provide transparency to their customers regarding costs, investment strategies, and involved risks. In addition, companies have to collect information about the securities-related knowledge, experience, investment strategy, and financial background of customers to provide an eligible investment strategy or financial instrument. Furthermore, Article 33a WpHG defines best execution policies for companies which provide financial services referring to costs, speed, and probability of order executions as dimensions of best execution.

Order execution and post trade services are regulated through the Stock Exchange Act (BörsG)[23] which obliges exchanges to provide transparency to their price fixing policies and the duty to execute orders in a fair manner with respect to the current market situation. Article 7 BörsG defines the obligation of exchanges to implement an independent trade surveillance office to ensure compliance with the Stock Exchange Act.

European Law

The Prospectus Directive (Directive 2010/73/EU) is the European framework for transparency guidelines regarding financial instruments. In Germany, it has been implemented through the WpPG. On July 3rd, 2012 the European Commission presented a regulatory proposal regarding the introduction of *Key Information Documents* (KID) for packaged retail investment products (PRIP). Such documents are similar to the German short version of product prospectuses as described in WpDVerOV.[24] Essential objective of this proposal is to increase transparency across different retail investment products through standardized understandable descriptions of product functionality, payoff, and risks.

The European Markets in Financial Instruments Directive (MiFID) was introduced in 2007 and allowed for increased competition in European financial markets through the introduction of alternative trading venues. MiFID provided a set of rules regard-

[22]German designation: Wertpapierhandelsgesetz.
[23]German designation: Börsengesetz.
[24]EU Source: `http://ec.europa.eu/internal_market/finservices-retail/investment_products_en.htm`. Accessed 03/14/2013.

ing market access, transparency, and best execution.[25] Best execution means that "investment firms take all reasonable steps to obtain, when executing orders, the best possible result for their clients taking into account price, costs, speed, likelihood of execution and settlement, size, nature or any other consideration relevant to the execution of the order."[26]

Corporate Responsibility

> *It would be naive to think that the certificate industry could provide satisfying transparency, since it is responsible for most grievances.*
>
> - Schutzgemeinschaft der Kapitalanleger e.V., Schwarzbuch Börse 2009

Almost all German issuers of structured products are members of the German Derivatives Association.[27] DDV is a representative organization aiming to improve the understanding and acceptance of structured products in Germany and Europe. In conjunction with several similar associations from Austria, France, Italy, Switzerland, and Sweden it builds the umbrella organization European Structured Investment Products Association. All members of the DDV committed themselves to comply with the Derivative Code, which has been approved by the DDV on January 1, 2007. The Derivative Code defines a set of rules regarding issuance, sales, marketing, and trading of structured products as follows (Deutscher Derivate Verband, 2007):[28]

- The creditworthiness of the issuer is always communicated openly
- The underlying is presented transparently
- Derivatives information must ensure product clarity
- Derivatives securities are offered at prices that are fair in relation to the product structure and market situation

[25]See Davies et al. (2005) for a detailed overview of MiFID. On October 26, 2012 the European Parliament approved a revised version of MiFID, MiFID II. MiFID II focuses on regulation of High Frequency Trading (HFT).

[26]Quote extracted from Article 21 of the Directive 2004/39/EC. See, e.g., `http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2004:145:0001:0044:EN:PDF`. Accessed 09/26/2013.

[27]A list of members can be obtained here: `http://www.derivateverband.de/ENG/TheAssociation/MembersAndSponsoringMembers`. Accessed 03/14/2013.

[28]The Derivative Code is found at `http://www.derivateverband.de/ENG/Policy/TheDerivativesCode`. Accessed 03/14/2013.

- Every signatory ensures that its derivative securities are tradable
- The signatories of this Code of Conduct undertake to observe it at all times

Concluding, all regulatory approaches, national, international as well as corporate initiatives, try to tackle the issue of transparency in the market of structured products. However, the ongoing debate of missing transparency and increasing complexity of structured products leaves both investors and regulators with doubts regarding the efficiency of the current regulation.[29]

Listing Fees

A fundamental driving factor behind market transparency are the issuance costs for investment banks, influencing the magnitude and clarity of the market of structured products. The lower the costs the more products can be issued, which could result in increased obfuscation of investors. Generally, issuance costs consist of implicit and explicit costs. Implicit costs are, for example, salaries of the staff, which is responsible for issuance and hedging of products. Additionally, hedging of positions results in transaction costs and costs of capital. Explicit fees are the initial issuance registration with regulatory institutions, such as the BaFin in Germany, and listing fees at exchanges. In Germany, BaFin charges an initial fee of EUR 6,500 for each basis prospectus and an additional fee of EUR 1.55 for each issuance of a structured product. Each investment bank only needs one basis prospectus for each overall product type, such as bonus certificates for example. This section focuses solely on observable explicit costs that arise at exchanges, i.e. listing fees.

Listing fees vary substantially between countries ranging from strict linear pricing structures to flat rates. The following subsections provide an overview of different fee structures across Europe. I report listing fees for each country based on the fee structure of the exchange which has the most market share in the respective country.

[29] For example, see http://www.risk.net/structured-products/feature/2273915/structured-products-nordics-swedens-regulator-demands-greater-transparency and http://www.fsma.be/en/in-the-picture/Article/nipic/nipic_tsspersonen.aspx. Accessed 06/22/2013.

Germany The leading German exchange for structured products is Stuttgart Stock Exchange with a market share of roughly 60%.[30] Generally, listing is distinguished by market type: regulated unofficial market vs. regulated market. Most products are issued within the regulated unofficial market, allowing issuers to be more flexible with respect to information provision. Both market types have in common that listing fees are capped after the first 200 products up to 5,000 products. Marginal costs for products exceeding this number are EUR 0.60 (EUR 0.90) for the regulated unofficial market (regulated market). Table 2.2 shows the listing fee structure for Stuttgart Stock Exchange.[31] Obviously, such low marginal costs for high listing numbers are negligible for issuers, thus I speak in the following of a flat rate for the German market for higher numbers of issued products.

TABLE 2.2: **Listing Fees Germany.** This table shows costs for the listing of structured products at the Stuttgart Stock Exchange located in Germany.

	Fee per Product [EUR]	
#Products per Year	Regulated Unofficial Market	Regulated Market
$1 - 200$	250.00	375.00
$201 - 5{,}000$	0.00	0.00
$> 5{,}000$	0.60	0.90

Switzerland As pointed out before (see Section 2.3), referring to turnover, the Swiss market is the second most developed market for retail investors in Europe. However, the number of tradable products is substantially smaller compared to Germany. Looking at Figure 2.9 and 2.10 points out the difference in listing fees.[32] In contrast to Germany, marginal fees for higher listing numbers at the SIX Swiss Exchange, the Swiss leading exchange, are not close to zero, resulting in considerably higher total costs for issuers. Fees are different depending on the time to listing. Issuers aiming for their products to be tradable at the following day (T+1) have to pay CHF 1,900 for each product. Products to be tradable three days after the listing application (T+3)

[30]Market share refers to exchange traded turnover. Source: DDV Statistic May 2013, `http://www.derivateverband.de/DE/MediaLibrary/Document/PM/05%20B%C3%B6rsenumsatzstatistik%20Mai%202013.pdf`. Accessed 06/20/2013.

[31]Information on fees is obtained from `https://www.boerse-stuttgart.de/de/boersenplatzstuttgart/regelwerke/regelwerke.html`. Accessed 06/21/2013.

[32]Information on fees is obtained from `http://www.six-exchange-regulation.com/admission_manual/10_01-LOC_en.pdf`. Accessed 06/24/2013.

are charged a lower fee of CHF 1,700. Besides this linear pricing structure issuers can buy listing packages, which allow for the listing of a number of products up to the given package size within 12 consecutive days. The package price is fixed independently from the number of products that have actually been issued. Table 2.3 reports different package fees. Products purchased through packages are partly of type T+1

TABLE 2.3: **Swiss Package Listing Fees.** This table shows costs for the listing of structured products at the SIX Swiss Exchange located in Switzerland.

Package Size	Fee [CHF]	Fee p. Product [CHF]	Transformation Fee p. Product [CHF]
200	300,000	1,500	200
500	600,000	1,200	200
1,000	990,000	990	150
2,000	1,600,000	800	100
5,000	3,000,000	600	100
7,500	3,900,000	520	100
10,000	4,500,000	450	100

and T+3. The two smallest packages contain issuing rights for 20% T+1 and 80% T+3 products, whereas the remaining packages are split 25% to 75% between T+1 and T+3, respectively. In order to change the time to market from one type to the other, issuers have to pay a transformation fee for each product they want to transform.

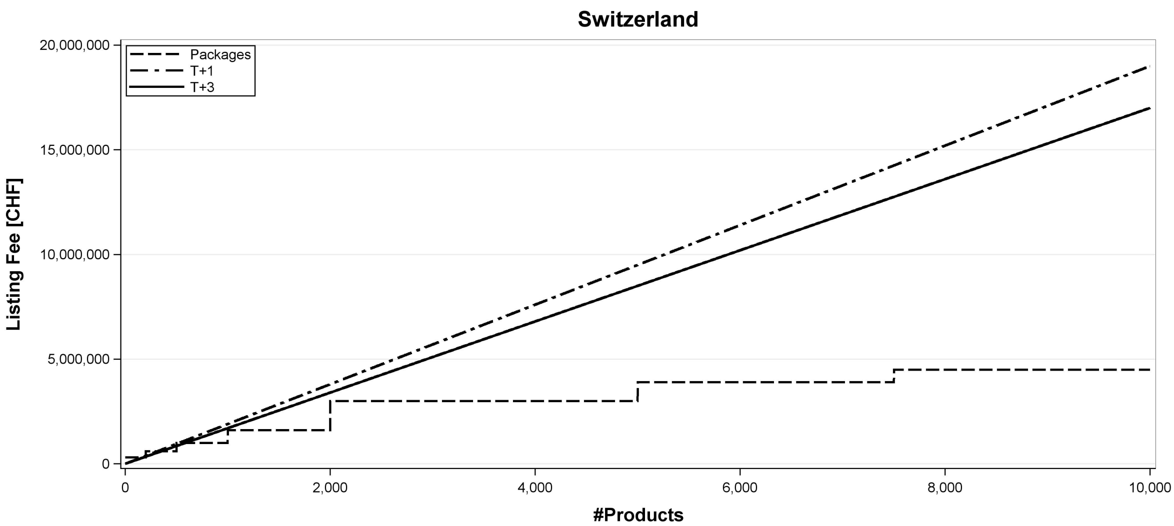

FIGURE 2.9: **Listing Fees Switzerland.** This figure visualizes listing fees for the SIX Swiss Exchange. Besides linear tariffs (T+1, T+3) and package tariff is provided.

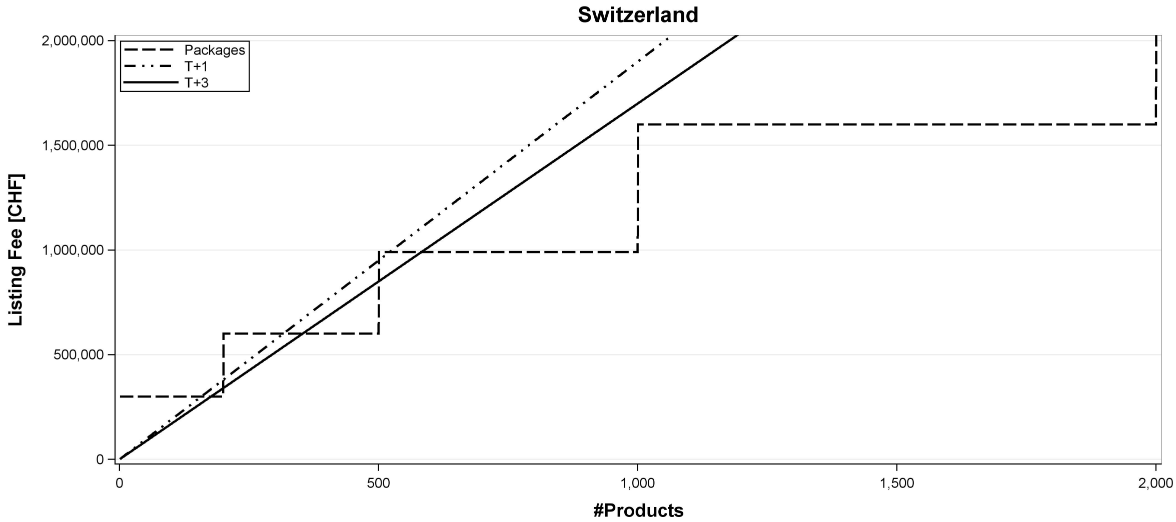

FIGURE 2.10: **Listing Fees Switzerland For Less Than 2,000 Products.** This figure visualizes listing fees for the SIX Swiss Exchange. Besides linear tariffs (T+1, T+3) and package tariff is provided.

Austria The Vienna Stock Exchange is the only stock exchange in Austria. It adds a new component to the discussed pricing structures: annual payments. Besides a one time payment for each listing, issuers have to pay annual fees for each product that has been tradable on at least one day in a calendar year. Table 2.4 provides an overview of those fees.[33] Although Austrian listing fees are lower in comparison to

TABLE 2.4: **Listing Fees Austria.** This table shows costs for the listing of structured products at the Vienna Stock Exchange located in Austria.

# Products p. Year	Fee p. Product (one time payment) [EUR]	Fee p. Product (annual) [EUR]	Total Fee p. Product [EUR]
1 − 350	145	58	203
351 − 700	140	50	190
701 − 1,000	120	40	160
1,001 − 1,500	100	30	130
> 1,500	80	25	105

Switzerland, they are still by far more expensive compared to fees in Germany.

[33]Information on fees is obtained from `http://www.wienerborse.at/listing/gebuehren/zertifikate.html` and `http://www.wienerborse.at/static/cms/sites/wbag/media/de/pdf/agb/agb_4.pdf`. Accessed 06/21/2013.

France The leading exchange for structured products in France is the merger of NYSE and Euronext. Listing fees for structured products are based on the total number of outstanding shares instead of the number of different products compared to exchanges described above (see Table 2.5).[34] The fee structure has similarities to those

TABLE 2.5: **Listing Fees France** This table shows costs for the listing of structured products at the NYSE Euronext Paris located in France.

Mio. Shares Outstanding p. Year	Fee (one time payment) [$]	Fee (annual) [$]
(0,1]	5,000	10,000
(1,2]	10,000	10,000
(2,3]	15,000	10,000
(3,4]	20,000	10,000
(4,5]	25,000	10,000
(5,6]	30,000	10,000
(6,7]	30,000	12,000
(7,8]	30,000	14,000
(8,9]	30,000	16,000
(9,10]	32,500	18,000
(10,15]	37,500	20,000
(15,25]	45,000	25,000
(25,50]	45,000	42,000
> 50	45,000	55,000

of the Austrian and Swiss exchanges. It consists of both a one time payment on listing and an annual fee for each product, similar to the Austrian market. Additionally, the fee structure is a step function that is indifferent between numbers of shares outstanding within each group, which resembles the Swiss package fee structure. However, marginal costs for listings of more than 50 million outstanding shares are zero, thus resulting in a flat rate for issuers. Therefore, the total costs are capped at EUR 100,000 per year and issuer. Assuming a fixed number of outstanding shares per product, Figure 2.11 visualizes the listing fee structure.

Sweden Listing fees in Sweden consist of a one-time payment of SEK 3,000 per product, capped at SEK 15,000 for each "listing occasion"[35] and an annual fee based

[34]Information on fees is obtained from `http://www.nyse.com/pdfs/NYSEArca_Listing_Fees.pdf`. Accessed 06/21/2013.

[35]Information on listing fees was provided through personnel of the Nordic Derivatives Exchange (NDX). The term "listing occasion" is not specified in more detail. In the following I assume this to be a daily limit.

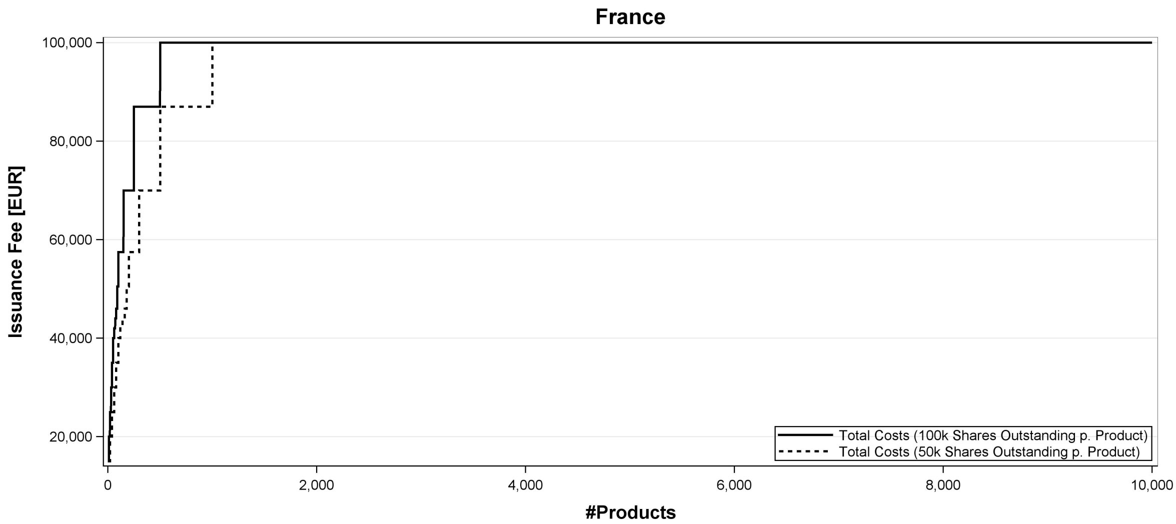

FIGURE 2.11: **Listing Fees France.** Listing fees are calculated based on the assumption of a fixed number of outstanding shares per product. The dashed line denotes fees for an assumed number of 50k shares outstanding per product, whereas the solid line visualizes fees for twice the number of shares oustanding.

TABLE 2.6: **Listing Fees Sweden.** This table shows costs for the listing of structured products at the Nordic Derivatives Exchange located in Sweden.

Nominal Value [Million SEK]	Annual Fee [SEK]
(0, 25]	4,500
(25, 50]	6,000
(50, 100]	8,000
(100, 200]	10,500
> 200	13,500

on the total nominal value issued per product as reported in Table 2.6.

Italy At the Borsa Italiana listing fees are dependent on the admission process used for issuing products: via SeDeX, online, or offline (paper based).[36] Overall, all approaches have in common that listing fees are only capped per "series"/listing.[37] There are no annual payments for all outstanding products and no flat rate. As for

[36]Information on fees is obtained from `http://www.borsaitaliana.it/azioni/come-quotarsi/listing-fees/listingfees01102012eng.en_pdf.htm`. Accessed 07/22/2013.

[37]The term "series" is not explicitly defined in any official document available to me. However, it probably refers to all products issued at once with the same underlying.

TABLE 2.7: **Comparison of Listing Characteristics.** This table captures fee characteristics for the listing of structured products of several European exchanges. The following symbols are used: ● denotes that statements of the first column are valid for the individual fee structure, whereas ○ denotes the opposite. If the fee structure includes a similar approach it is flagged with ◐.

	Germany	Switzerland	Austria	France	Sweden	Italy
Packages	○	●	○	●	○	◐
Fees for single listings	●	●	●	○	●	●
Flat rate (approximately) for higher numbers	●	○	○	●	○	○
Annual costs	○	○	●	●	●	○
Fees depending on total shares outstanding	○	○	○	●	●	●
Reduction of fees with increasing number of products per year	●	◐	●	●	●	○

the listing via SeDeX fees are "0.05% of the raised amount per each series" with a cap of EUR 20,000 and a floor of EUR 5,000.[38]

Comparison Listing fees across European exchanges are very heterogeneous, combining different pricing structures and reference values for the fee calculation. Table 2.7 provides an overview of different fee characteristics across countries.

Besides the Borsa Italiana, all exchanges have a reduced fee for an increasing number of issued products. However, only Germany and France provide a flat rate tariff for issuers. This clearly leaves Austria and Switzerland with the highest listing fess in Europe. Differences in the amount of the costs between countries may be motivated by competition between national exchanges. In Germany, Scoach and Stuttgart are competing for order flow, whereas in other countries structured products can only be traded at a single exchange. One benefit of lower listing fees is the increased product variety for investors, which allows for a better fit of individual risk-return perceptions. Investors can often choose between hundreds of products that fit their search criteria. However, studies such as Wilson and Price (2010) and Miravete (2004) argue that consumers are overwhelmed by available alternatives and do not necessarily make the best decision in return. I analyze the product variety with respect to

[38]If two series are issued fees for one of those series with a distribution volume of less than 10 million are waved.

potentially occurring search costs in Section 5.4.5.

2.5 Summary

In this chapter, I provide details on the market structure for structured products in Germany and the product universe including market statistics and descriptions for different investment and leverage products. Germany and Switzerland are by far the most dominant markets with respect to retail investor trading volume in Europe. However, only Germany experienced a product boom in the last years with more than 1 million products in 2013. Additionally, I summarize the current regulatory environment with a focus on the listing fees in different European countries. Based on these findings it can be concluded that one reason for the vast development in Germany is the substantially lower listing fees compared to all other European countries.

Chapter 3

Behavior of Participants

There have been various studies analyzing the human behavior in financial markets. Due to technological advances in trading infrastructure, -services, and -interfaces, as well as in financial markets itself, retail investors are no longer depending on brokers or expensive routing systems, but are able to trade independently in a similar way compared to a professional trader at an investment bank. As a consequence of this independence, financial research has increasingly studied trading behavior of small investors. Along with that, markets have been rising that allow small investors to invest their capital beyond simple financial instruments such as stocks or funds.

3.1 Issuer Behavior

This section presents related work regarding the behavior of investment banks in the market for structured products. First, I summarize relevant literature studying the pricing of structured products. Second, articles examining information provision as influencing factor are discussed.

Pricing of Structured Products

In 1989 HSBC Trinkhaus issued the first structured product in Germany, and thus gave up for the vast development of this market.[1] As pointed out in the former sec-

[1] Information is obtained from an official Scoach press release available at `http://www.scoach.de/en/arcmsdownload/0f8391702c075eb84efe91f0d487e674/CONTENT.pdf/scoach-`

tion, prices for such retail investor products are set by the issuing investment bank. Since the '90s several studies have examined this market more or less deeply with respect to pricing methods of issuers. Until today, issuers lack transparency for the pricing policies of their products. In general, four major studied research questions can be distinguished in the literature:

1. Are there any price deviations between issuers' quoted prices and theoretically derived (fair) prices?
2. Do price deviations change over the life time of products?
3. Does order flow of investors influence price deviations of issuers?
4. Are there any intraday pricing changes of issuers?

Table 3.1 provides a brief overview about existing empirical and theoretical studies analyzing price discrepancies of structured products for several markets worldwide with respect to these research questions. Question 1 generally addresses the assumption that issuers set higher prices for their products than their theoretical fair values. Research question 2 has been studied as a proxy for the third question, since trading data of retail investors, which is representative for the issuers' customers has not been available for most studies. Assuming that retail investors tend to enter more positions than exit positions in the beginning of a product's life time, and the other way around towards the end, a decrease of overpricing with shorter time to maturity results in higher buy prices and lower sell prices for retail investors. This decrease in overpricing (premium) denotes the hidden margin of issuers. This phenomena is also known as life cycle effect. Question 4 addresses potential anticipation patterns of issuers during the trading day and is thus similar to the third question. Due to the variety of product types and issuers such research questions have not been answered for the whole market, but only for small sub samples of different markets.

In 1990 investment banks begun to issue single products in the US market. Those first structured products were capital-guaranteed products and build through the combination of a (risk-free) bond and an index option. Chen and Kensinger (1990) carried out the first study for those products. They analyze 18 respectively 24 market-index certificates of deposit on two different days for two different issuers. In-

hsbc-intraday-20090331-en.pdf. Accessed 06/25/2013. For a more detailed overview of the related derivatives history see Meier and Sandmeier (2012).

stead of duplicating the actual prices, the authors calculate the implied volatility values for those products and compare them to implied volatility values derived from exchange-traded index options. Since it holds for plain vanilla options that the higher the implied volatility the higher the price of the option, results of this approach can be interpreted in a similar way compared to the calculation of theoretical option prices. As a result, Chen and Kensinger observe substantial deviations between implied volatilities of structured products and traded index options. Additionally, they observe that implied volatility even deviates among products of the same issuer. Chen and Sears (1990) complement this first study with respect to time as a driving factor through the analysis of one single index note on the S&P 500 over a longer horizon. An index note denotes the combination of a bond and a weighted call option. They calculate theoretical prices for bond and option value for three different sub periods. They find that price deviations are different between sub periods, with seven times higher deviations in the first period compared to the second period. However, due to the financial market crash in 1987, which lies within the third sub period, prices of the first two periods are hard to compare with prices of the last period. Nevertheless, this seems to be early evidence for non-constant premiums during the life time of structured products.

Burth et al. (2001) investigate a sample of 275 reverse convertibles in the Swiss market. All of those products have a similar payoff structure, consisting of a long investment in the underlying and a short position in a call option on the same asset. Reverse convertibles are converted into shares of the underlying asset, if possible, if the underlying falls to a predefined level. If the barrier has not been touched investors receive 100% of their invested value plus potential coupon payments. On average they observe a premium of 1.91%. Differentiating by issuer, premiums range from 0.02% to 6.29%. Products, which pay regular interest include a higher premium (3.22%) compared to those without a coupon (1.40%).

Easton et al. (2004) study quotes of a small set of barrier options on the Australian Stock Exchange in 1998. They find higher overpricing in barrier options compared to plain vanilla options, relative to their chosen model. However, whether or not such products are traded by retail investors remains unknown to the reader. Grünbichler and Wohlwend (2005) conduct a more sorrow analysis, based on 192 Swiss "concave" products from April 14, 1999 until March 30, 2000. They find higher implied volatility differences for the primary market compared to the secondary market, but overall still to investors' disadvantage.[2] Similar to earlier studies, they find that price deviations are substantially different between issuers. However, all issuers price products to their own advantage on both the primary and the secondary market. Supporting Burth et al. (2001) they find that products with coupon payments experience a higher mispricing than products without. In addition, Grünbichler and Wohlwend group quotes of products by time to maturity into 5 sub periods and observe a "significant time-dependent valuation pattern in the secondary market that affects all the product categories".[3] They conclude that issuers "[...] are making rational use of their quasi-monopolistic position".[4]

Wilkens et al. (2003) were first to carry out a representative study for two major product types in the German market.[5] They analyze price discrepancies of 170 reverse convertibles and 740 discount certificates using data from 2001. They find for both product types quoted prices to be deviating substantially from prices derived through duplication. On average, quoted prices favor the issuer with overpricing being 3.04% for reverse convertibles and 4.20% for discount certificates. Additionally, the authors associate price deviations to the life time of products, using the life cycle as proxy for possible order flow tendencies: Retail investors tend to buy products at the beginning of the life time and sell it towards the end. They find that overpricing decreases with shorter time to maturity. Stoimenov and Wilkens (2005) extended this study to include several other product types, more precisely, plain-vanilla products, barrier products, and rainbow products.[6] They observe for all product types substantially higher issuance prices. Product types including barrier options incorporate higher premiums compared to products solely build of classic plain vanilla options. For most product types they find evidence that issuers are decreasing overpricing with decreasing maturity.

[2]In this context, primary and secondary market refers to the Swiss regulation. After issuance, products can be traded at regulated exchanges, i.e. the secondary market. Before issuance, products can be 'distributed' in the primary market, which is not fully subject to the Swiss Stock Exchange Act.

[3]Grünbichler and Wohlwend (2005), p. 378.

[4]Grünbichler and Wohlwend (2005), p. 378.

[5]Earlier papers discussing German structured products are based on very small samples if any, for example Wilkens and Scholz (2000).

[6]Products with a *rainbow* option have a basket of underlying assets. The payoff follows specific rules that weigh the different underlying assets. Rainbow products are often referred to as exotic products.

Scholz et al. (2005) contribute to the existing literature through the analysis of overpricing for 23 call and put knock-out warrants issued by ABN AMRO. They find that the issuer quotes products above theoretical values, and sometimes even higher than described in his product prospectuses. The authors calculate overpricing for two different dates and show that premiums are decreasing with shorter time to maturity. Benet et al. (2006) study so-called reverse-exchangeable securities issued by ABN AMRO for the US market. They find that reported quotes are overpriced on average. However, they conclude that premiums may be adequate for the service issuers provide and the additional risk for issuers due to a more complicated hedging strategy.

Muck (2006) analyzes differences of overpricing between exchange-traded products (Knock-out warrants[7]) and OTC products (ClickOptions[8]) over a period of roughly two months. He observes higher premiums for OTC prices compared to premiums of exchange-traded products. However, he finds only little evidence for the life cycle effect for both OTC and exchange-traded products. Wilkens and Stoimenov (2007) provide further evidence for the German market for leverage products. They find that issuers earn (almost) risk-free profits, assuming investors to perform classic buy-and-hold strategies. Premiums for put products are higher compared to call products. Furthermore, they find that quoted prices are even higher than calculated prices for a semi-static hedging strategy of issuers.[9] Baule et al. (2008) study overpricing of discount certificates on February 27, 2004. They focus on different pricing models and credit risk as influencing factor of issuers' premiums. They observe rather low premiums, ranging between 0.84% and 2.39%, depending on issuer and selected model.

Entrop et al. (2009) study overpricing of open-end leverage products based on the pricing methodology communicated by issuers. Characteristics of products that do not have a fixed maturity date are adjusted regularly. For example, the knock-out barrier of a call knock-out warrant is raised on specific event dates. Entrop et al.

[7]Originally, Muck refers to *Turbo certificates* as subject of his analysis. However, this is just a different label for knock-out warrants.

[8]ClickOptions, a platform to trade digital options, owned by Société Générale, shut down its services on 04/09/2010.

[9]Semi-static hedging strategies require only a single adjustment of the issuer's portfolio compared to dynamic hedging.

find that price setting formulas for open-end products are designed to incorporate an increasing profit over the product life time, which is a similar effect compared to the known life cycle effect for products with fixed maturity dates. Issuers are theoretically able to gain profits of 20-30% per year, depending on investor demand and issuance behavior. Rossetto and van Bommel (2009) conducted a similar study for the same product type. They analyze 5,129 leverage products written on DAX30 stocks in January 2007. Compared to Entrop et al. (2009) they find only small differences between intrinsic values and quoted prices, with quoted prices ranging between 0.3% and 3% higher than theoretical values. However, the sample period does not allow for a representative picture across the life time of such products.

Szymanowska et al. (2009) analyze reverse convertibles in the Dutch market and observe an overpricing of 5% across issuers and products, which were tradable between January 1, 1999 and December 31, 2002. Wallmeier and Diethelm (2009) support those findings for the Swiss market. They analyze 468 reverse convertibles with multiple barriers, tradable in April, 2007. Overall, they observe a premium of 3.4% on average. Concluding, the authors state that "[...] investors tend to overestimate the importance of a sure coupon payment and underestimate the risk involved."[10]

Henderson and Pearson (2010) provide a recent study on Stock Participation Accreting Redemption Quarterly-pay Securities (SPARQS) in the United States. SPARQS are callable bonds, including quarterly coupon payments, that are returned in shares of the underlying asset upon maturity. After a defined period the issuer has the right to call the security and pay investors a predefined maximium profit, which is at least the sum of all coupon payments. On average, premiums are at least 8%. The authors argue that SPARQS are not traded for tax benefits or liquidity reasons. Expected returns of SPARQS are observed to be less than the actual risk-free rate, which makes it unbelievable for informed investors to trade them.

Instead of focusing solely on product life time as proxy for customer order flow, Baule (2011) uses aggregated buy and sell orders of investors to prove that issuers' quotes are influenced by the net trading volume of investors. For the daily imbalance measure he observes a decrease of premiums if issuers expect a positive order flow, i.e. more buy than sell orders, and lower premiums the other way around. During

[10]Wallmeier and Diethelm (2009), p. 70.

this sample period the German fiscal system did not charge profits generated through certificates that were hold for more than one year with a tax. Baule finds that, generally, issuers anticipate both the life cycle effect and the tax effect, although not all of them anticipate both.

Baule and Tallau (2011) apply different variations of the classic Black-Scholes model as well as the Heston model to the pricing of bonus certificates. They observe that issuers seem to incorporate the volatility skew into their prices, but they do not find any evidence that issuers rely on the Heston model. They find premiums, based on the Heston model, to be between 2.1% and 4.9% depending on the issuer. Bernard et al. (2011) study locally-capped products in the U.S., which are similar to bonus certificates. They provide evidence that premiums are on average 6.5%.

Entrop et al. (2011) are first to analyze intraday price setting behavior of investment banks for structured products. They use a trade data set of a direct bank and calculate premiums of leverage products for the German market in 2007 and 2008. They find a general overpricing of leverage products and provide evidence for the life cycle hypothesis. Furthermore, issuers seem to increase premiums towards the end of the day, further increasing them after the closing prices of the underlying. In contrast to former studies, they rely on a proprietary data set provided by a direct bank, instead of quoted prices at a regulated exchange.

Concluding, most academic studies find significant positive premiums for different product types and periods. Premiums vary across issuers, product types, and the remaining time to maturity. However, only little evidence is presented focusing on a direct measurement of investor anticipation by issuers.

TABLE 3.1: **Related Work - Pricing of Structured Products.** This table captures related literature to the pricing of structured financial products. Results are reported for the categories *Overpricing (OP)*, *Life cycle effect (LCE)*, *Intraday effect (IE)*, *Demand effect (DE)*. If results support the assumption of the respective category it is flagged through ●. If a category was analyzed, but results do not support the effect it is marked with ◐. ○ denotes that the effect was not studied in the paper.

Article	Product Types	#Products	Period	OP	LCE	IE	DE
Chen and Kensinger (1990)	Index certificates of deposit	18/24	01/1988; 01/1989	●	○	○	○
Chen and Sears (1990)	Indexed Note (SPIN)	1	09/01/1986 - 12/31/1987	●	○	○	○
Burth et al. (2001)	Reverse Convertibles	275	08/01/1999	●	○	○	○
Wilkens et al. (2003)	Reverse Convertibles,	169	11/01/2001 - 11/30/2001	●	●	○	○
	Discount Certificates	737	11/01/2001 - 11/30/2001	●	●	○	○
Easton et al. (2004)	Barrier Warrants	8	08/1998 - 09/1999	●	○	○	○
Grünbichler and Wohlwend (2005)	Investment Products	192	04/14/1999 - 03/30/2000	●	◐	○	○
Stoimenov and Wilkens (2005)	Several	2,566	08/31/2001 - 10/10/2002	●	●	○	○
Scholz et al. (2005)	Knock-out Certificates	23	05/15/2003, 09/26/2003	●	●	○	○
Benet et al. (2006)	RES	31	06/2001 - 07/2003	●	○	○	○
Muck (2006)	Turbo certificates	334	12/11/2003 - 01/23/2004	●	◐	○	○
	ClickOptions	393	12/11/2003 - 01/23/2004	●	◐	○	○
Wilkens and Stoimenov (2007)	Stock/Index Certificates	279(219)	01/01/2004- 06/30/2004	●	○	○	○
Baule et al. (2008)	Discount Certificates	1,722	02/27/2004	●	○	○	○
Entrop et al. (2009)	Open-end Leverage Certificates	-	-	●	●	○	○
Rossetto and van Bommel (2009)	Open-end Leverage Certificates	5,573	January 2007	●	○	○	○
Szymanowska et al. (2009)	Reverse Convertibles	108	01/01/1999 - 12/31/2002	●	○	○	○
Wallmeier and Diethelm (2009)	Reverse Convertibles	468	April 2007	●	○	○	○
Henderson and Pearson (2010)	SPARQS	64	06/2001 - 12/2005	●	◐	○	○
Baule (2011)	Discount Certificates	4,451	11/2006 - 12/2007	●	●	○	●
Baule and Tallau (2011)	Bonus Certificates	1,057	11/1/2006 - 08/29/2008	●	●	○	○
Bernard et al. (2011)	Locally Capped Products	29	04/2008	●	○	○	○
Entrop et al. (2011)	Leverage Products	18,490	2007 - 2008	●	●	●	○

Information Provision

Current regulation and supervision require issuers to provide information about their financial instruments and involved risks (see Section 2.4). According to MiFID, European issuers have to act in an honest, fair, and professional manner to ensure providing a service in the best interest of investors. In Germany, this includes the publication of short prospectuses that should provide all essential information regarding the financial instrument. However, the way of presentation might be biased and thus influencing retail investors.

Breaban et al. (2012) conduct an experimental study with more than 500 undergraduate students from different fields to examine the effect of shown scenarios of financial instruments on the decision-making process. They find that the amount of information, which is available and its way of comparability affects retail investors in their decision. Bernard et al. (2011) analyze hypothetical scenarios presented in product prospectuses for locally capped products in the US. They find that issuers often illustrate scenarios that are "extremely optimistic and conjecture that this may contribute to the popularity of these products".[11] Olazábal and Marmostein (2010) as well show concerns that unrealistic scenarios might leverage investors' innumeracy and cognitive biases in form of inconsiderate investments. They favor a stronger regulation for the market for structured products "to weed these unwise products [,principal protected notes,] out of the marketplace" and thus "protecting the unsophisticated retail investor from the inevitably mistaken inferences that motivate their purchases".[12] Contradicting to these studies, Baule et al. (2012) find, studying more than 20,000 product prospectuses for the German and US market, that issuers illustrate their products through scenarios that are conservative or even negatively biased. Additionally, they run an experimental study to analyze the influence of shown scenarios on the perceived future return of a financial instrument. Again, opposed to Olazábal and Marmostein (2010) they do not find any evidence that investors' perceived return is influenced through biased scenarios.

Although, from an academic perspective the discussion about the influence of biased information in product prospectuses remains unsettled, current regulatory de-

[11]Bernard et al. (2011), p. 86.
[12]Olazábal and Marmostein (2010), p. 665.

bates demand the exposure of more inside information. The board of the International Organization of Securities Commissions (IOSCO) published in April 2013 a consultation paper, which supports the discussion about the disclosure of hidden fees and fair values of structured products.[13]

3.2 Retail Investor Behavior

Traditional financial theory states that market participants are fully rational and act according to specific utility functions. However, numerous studies report results that cannot be entirely explained by this traditional perspective. In order to overcome this gap between theoretical expectations and practical outcomes, the field of behavioral finance/economics studies effects of cognitive, social, and emotional factors on the decision making process of individual investors. First, I provide a literature overview of studies analyzing retail investor trading performance. Evidence for investors' choice between aggressive and passive orders is examined afterwards. Finally, I describe prominent behavioral biases and decision-making failures, which are of importance for the understanding of results in this thesis.

Performance and Investor Wealth

Retail investor performance in financial markets is ambiguous. Traditional literature often characterizes small investors as noise traders, who hold under-diversified portfolios. However, several more recent studies find that retail investor trades often positively predict future returns and thus generate profits on average. Table 3.2 provides a brief overview of the literature discussed in the following.

Odean (1999) is one of the pioneer studies regarding retail investors and behavioral finance. He analyzes brokerage accounts of 10,000 retail customers from a large discount broker in the USA. The sample period ranges from 1987 until 1993 and includes every change in portfolio positions for those customers. He finds that retail investors trade excessively and reduce their returns as a consequence. Controlling

[13]See `http://www.iosco.org/library/pubdocs/pdf/IOSCOPD410.pdf`. Accessed 06/26/2013.

for "[...] liquidity demands, tax-loss selling, portfolio rebalancing, or a move to lower-risk securities, trading still lowers returns."[14] Barber and Odean (2000) support those former findings with a similar more recent data set. They observe that retail investors have an average return of 3.7% less than the market return, and even worse for investors trading more than average. On average, investors have a yearly turnover of 75% of their portfolio. Barber et al. (2009) analyze long and short term returns of investor trades. Compared to previous studies they do not have brokerage account data, but use trades below $ 5,000 as proxy for retail investor trades. They find mixed results regarding return prediction over short and long term horizons. Stocks bought in one week have positive abnormal returns for the following two weeks. The opposite holds for stocks that have been sold. From an annual perspective, stocks bought by retail investors have lower returns than stocks sold.

Kaniel et al. (2008) find similar patterns for short-term horizons. They study a sample of NYSE stocks from 2000 until 2003 and find that prices of stocks heavily bought by investors in a month increase in the following month, and vice versa. Using the same data set, Kaniel et al. (2012) study informed trading of investors around earnings announcements. They find "[...] that intense aggregate individual investor buying (selling) predicts large positive (negative) abnormal returns on and after earnings announcement dates."[15] Barber et al. (2009) study Taiwanese trading data ranging from 1995 until 1999. This data set includes all transaction data in Taiwan and thus enables to differentiate easily between investor types. Building an imbalance measure to capture the cumulative returns for different investor groups, they observe a poor retail investor performance compared to institutional traders, having an abnormal return of -3.8% per year. "Buy low, sell high" is a popular saying in the financial industry. The capabilities of investors succeeding accordingly is called market timing. Barber et al. (2009) observe that market timing is responsible for 7% of losses by retail investors. Conversely, Kelley and Tetlock (2012) find that daily order imbalances of individual investors predict positive abnormal stock returns at the monthly horizon, with no evidence of return reversal.

Seasholes and Zhu (2010) examine whether retail investors have private information on locally headquartered companies/stocks. They find that buy transactions

[14]Odean (1999), p. 1296.
[15]Kaniel et al. (2012), p. 677.

underperform significantly sell transactions of customers. In addition, they calculate calendar-time portfolios with resulting alphas being zero, i.e. investors do not achieve better returns than the market itself.

Most studies focus on equity trading of retail investors. However, Bauer et al. (2009) analyze option trades of retail investors and find that, on average, losses in option trading are worse compared to equity trading. Nevertheless, they are able to identify a group of investors who consistently outperform their fellows and thus leave room for informed traders among retail investors.

Entrop et al. (2012) study retail investor performance in leverage products in the German market. The data set includes trades from "[...] a large German online broker with a huge base of several hundred thousands retail customers".[16] Including implicit and explicit transaction costs they observe capital-weighted negative returns for both warrant trading and knock-out warrant trading. On average, retail investors lose 0.85% when trading warrants, and 2.16% when trading knock-out warrants. Entrop et al. (2013) extend the former analysis focusing on investment products, in particular bonus and discount certificates. They observe risk-adjusted returns of about -3% (-10%) for discount (bonus) certificates.

To this day, the discussion about retail investor skills and the possible informational advantage or forecasting abilities remains unsettled. Recent findings contradict traditional beliefs that retail investors are simply noise traders, losing money over time. Several explanations have been proposed in the literature to connect those contradicting findings. In particular, Kelley and Tetlock (2012) argue that varying trading skills between customers of different brokers and learning effects may have influenced studies about retail investor performance. In addition, limitations in available data might have caused biased inferences about the general population of individual investors.

Aggressive vs. Passive Orders

Investors choice of order types has been a subject of numerous studies, focusing on the information content of each order type and its implications on order book dy-

[16] Entrop et al. (2012), p. 8.

TABLE 3.2: **Related Work - Retail Investor Performance.** This table captures findings regarding short (ST) and long term (LT) performance of retail investors for different traded securities.

Article	Country	Period	LT	ST
Stocks				
Odean (1999)	USA	1987 - 1993	-	
Barber and Odean (2000)	USA	1991 - 1996	-	
Kaniel et al. (2008)	USA	2000 - 2003		+
Barber et al. (2009)	USA	1983 - 2000	- / +	+
Barber et al. (2009)	Taiwan	1995 - 1999		-
Seasholes and Zhu (2010)	USA	1991 - 1996	-	
Kaniel et al. (2012)	USA	2000 - 2003		+
Kelley and Tetlock (2012)	USA	02/26/2003 - 12/31/2007		+
Options				
Bauer et al. (2009)	Netherlands	01/2000 - 03/2006		-
Structured Products				
Entrop et al. (2012)	Germany	05/2007 - 12/2008		-
Entrop et al. (2013)	Germany	02/2004 - 12/2008	-	

namics and liquidity. Overall, two basic order types exist: Market orders and limit orders. A market order is executed immediately for the best price possible at that moment. A limit order includes an additional limit price, which provides an upper (lower) threshold for a buy (sell) order. If a limit order cannot be executed right away it is visible in the order book, whereas a market order is never shown in the order book.

In general, these basic order types can be distinguished along the arising risks: Price uncertainty vs. execution uncertainty. Investors aiming for an immediate execution due to a possible short-time informational advantage would probably choose a market order. A market order is executed against the current best bid or ask, depending on the trade direction. If the order size exceeds the volume at the best bid or ask, the remaining volume will be retrieved from the following order book levels. Thus, the investor faces a risk of not knowing the execution price. In case of a very thin order book the execution price of a market order can therefore vary substantially. Investors using market orders pay the spread as price for an immediate execution. In the last years, several examples can be given for immediate price jumps in stocks due to the advancement of high frequency trading.[17] Using market orders does not protect investors of price jumps. On the other hand, using limit orders as an instrument to control for the execution price, leaves investors with uncertainty of execution. Investors have to monitor the status of their order and the corresponding order book situation to adjust their limit prices accordingly. If the limit of a order was hit the order gets executed if possible. For this to happen, the price of the instrument has to move into the direction of the limit price. This leaves the investor with the risk, that prices move still further in this direction, which is now opposite to the investor's position. This effect is called adverse-selection risk.

In case of many brokers, retail investors cannot submit a market order, but only a limit order with a limit price, which is immediately executable. Such orders are often labeled marketable limit orders. Market orders and marketable limit orders can be seen as aggressive orders, whereas standing limit orders are passive orders, waiting to get picked up by another trader. From a liquidity perspective, aggressive orders take liquidity, whereas passive orders reside in the order book and thus provide liquidity. Today, several other modifications of those two basic concepts are available, such as stop-orders or fill-or-kill orders. See Harris (2003) for a more detailed description of order types.

Similar to the discussion about retail investor performance, the situation with respect to the chosen order type does also not reveal a clear pattern in academic literature. Anand et al. (2005) find that institutional investors have a better performance when using limit orders compared to limit orders submitted by individual investors. The behavioral pattern of order type usage changes throughout the day. Market orders submitted by institutional investors in the first half of the trading day have a higher price impact than orders submitted in the second part of the day. Overall, performance of limit orders is better in the first half compared to the remaining day. Kaniel and Liu (2006) modify the Glosten and Milgrom (1985) model[18] to allow the choice of order type: Limit order vs. market order. They find that, given that infor-

[17]See the 'Flash-Crash' for example: `http://blogs.wsj.com/marketbeat/2010/05/11/nasdaq-heres-our-timeline-of-the-flash-crash/`. Accessed 06/26/2013.

[18]The Glosten and Milgrom (1985) model is a famous market microstructure model, involving a market maker and informed and uninformed traders. The market maker posts bid and ask prices at which he is willing to buy or sell shares. The market maker does not know whether incoming orders are informed or uninformed. He protects himself from losses through adjustment of his quotes: He increases prices after he sells shares, and lowers them after he buys shares from a trader.

mation is being long lived, informed traders prefer limit orders over market orders. An evaluation of trading in NYSE stocks supports their theoretical findings. Barber et al. (2009) find that losses by retail investors are mostly driven by aggressive orders, which make up for 64.9% of all trades. In contrast, institutional investors are profitable with both passive and aggressive orders. Linnainmaa (2010) studies the disposition effect, trading around earnings announcements, and investors contrarian behavior in Finland. He finds that negative effects for those three scenarios are to a huge extent driven by limit orders. For the sample period from 1998 until 2001 he observes positive (negative) returns for positions originating from market (limit) orders. Interestingly, those results are contradicting to Barber et al. (2009) for the Taiwanese market. Kelley and Tetlock (2012) find that only market orders correctly predict firm news and conclude that aggressive individual investor trading is informed, whereas passive individual investor trading provides liquidity when it is scarce. Both actions are found to have a positive impact on financial market efficiency.

Discussion Due to the differences in market structure and price discovery between classic stock markets and the German market for structured products, results above cannot simply be applied to the given market situation analyzed in this thesis. On highly liquid markets prices for stocks are determined through the order book, defining the current price as best bid and best ask of the order book. However, in markets where investment banks are the major liquidity supplier of their own financial products, order books contain only very few orders, if any. The current best bid and ask of a financial product is directly provided by the issuer. Therefore, intentions such as preventing huge price impacts through the use of limit orders should not matter. However, choosing between limit or market order as a question of immediacy and private information is still highly relevant for this market structure.

Belief and Behavioral Biases

Behavioral finance draws from the understanding that cognitive biases influence the decision making process of investors and thus drive outcomes to some extent away from good judgment or rational prediction. Barber and Odean (2011) provide a detailed overview of investor biases in the financial literature. In particular, overconfidence, sensation seeking, and limited attention are of importance for the context of my results.

Overconfidence Several psychological studies have shown that individuals tend to overestimate the value of their own information or their skills.[19] One of the best-known studies is Svenson (1981). He asked 160 students from Sweden and the USA how they would judge their driving skills and riskiness compared to other participants of the same experiment. They observed that 93% (69%) of American (Swedish) students "believed themselves to be more skillful drivers than the median driver [...] in their comparison group [...]".[20] Several papers show that overconfidence of investors leads to excessive trading. Barber and Odean (2001) base their analysis on psychological experience that men are on average more confident compared to women. They find that trading activity differs between gender, with man turning their portfolio by 77% per year compared to 53% for those portfolios belonging to women. For both men and women abnormal returns for portfolios throughout the year are smaller compared to their portfolios at the beginning of the year. The difference between genders is more pronounced if both are singles, compared to if they are married.

Sensation Seeking Grinblatt and Keloharju (2009) state that "[...] sensation seekers search for novel, intense, and varied experiences generally associated with real or imagined physical, social, and financial risks."[21] They analyze trading activity in Finland, using the number of speeding tickets as proxy for sensation seeking. They find that sensation seekers trade more, independently from their gender. Sensation seeking is also one motive to drive trading as entertainment purpose. Dorn and Sengmueller (2009) study trading records of German brokerage accounts including additional survey data for these customers. They find that "the most entertainment-driven investors trade about twice as much as those who fail to take pleasure in gambling or investing [...]."[22]

[19]See Moore and Healy (2008) for a comprehensive overview.
[20]Svenson (1981), p. 146.
[21]Grinblatt and Keloharju (2009), p. 550.
[22]Dorn and Sengmueller (2009), p. 602.

Limited Attention Standard asset pricing models are founded on the assumption that investors have infinite cognitive resources and thus correctly process incoming information immediately. However, in 1973 Kahnemann already pointed out that "attention is a scarce cognitive resource and attention to one task necessarily requires a substitution of cognitive resources from other tasks".

In a model of capital market equilibrium, Merton (1987) argues that investors are incompletely diversified because they are not aware of all available securities. Hence, less-known firms need to compensate investors with higher returns. Based on this reasoning, an increase in investor information demand leads to positive price pressure in the short-run and lower returns in the long-run. Barber and Odean (2008) find that retail investors "display attention-driven buying behavior".[23] They argue that investor attention exerts upward pressure on security prices. The rationale behind this is that retail investors can implement positive market expectations on any company by buying their stocks, whereas negative market expectations can only be transformed into trading decisions for stocks already held, due to the inability to sell short. As a result of this imbalance in buying and selling opportunities, retail investors are net buyers of stocks. Investors buy more than sell on days following extreme returns and news coverage of the bought asset.

Decision-making Failures

The decision process of the small investor is a frequently discussed topic in academic literature. Agarwal et al. (2006) find in an experiment that 40% of consumers are not capable of detecting the cheapest credit card option from an offered variety. Lambrecht and Skiera (2006) show that consumers of a German internet provider do not reduce costs given their consumption, but choose a more expensive contract. Similar results are yield by Malmendier and Della Vigna (2006) for the case of gym contracts. Decision failures are often induced through biases, as the flat rate bias, or the tendency to underestimate or overestimate individuals own consumption behavior. Wilson and Price (2010) analyze the UK electricity market and find that consumers choice of a electricity supplier does not comply with the rational minimization of costs, although, the market is fairly regulated and simple. Dorn (2010) finds that investors

[23] Barber and Odean (2008), p. 813.

choose poorly from a variety of similar warrants in the German market structured products. It seems that only high search costs or boundedly rationality can justify those findings.

Provider may profit from decision mistakes of investors on the short run through offering of more expensive options that are strictly dominated by others. Miravete (2004) was first to analyze the effects of this so called foggy pricing in the telecommunication industry. He finds that provider are offering tariffs that are strictly dominated by other own tariffs, but the number of dominated tariffs reduces with an increase of competition. In the following, two major decision-making failures are presented in more detail: The disposition effect and gambling.

Disposition Effect One of the most studied irrational trading patterns of individual investors is the disposition effect. Already in 1985 Shefrin and Statman captured the mere essence of the effect in their paper title: *The Disposition to Sell Winners Too Early and Ride Losers Too Long*. In other words, investors tend to hold on to stocks with a negative performance since they bought it, but sell profitable positions early instead of following a longer upswing. Odean (1998) introduced the standard methodological approach to capture the disposition effect as used in many later studies. He examines trading records for approximately 10,000 customers of a discount broker from 1987 to 1993. He finds strong evidence for the disposition effect and argues that other rational explanations such as past performance or higher transaction costs for lower priced stocks can be neglected. He proposes two alternative explanations for the existence of the disposition effect. First, it is a direct implication of the prospect theory as introduced by Kahneman and Tversky (1979). Prospect theory states that investors do not base their decision on the expected outcome but on the value of gains and losses itself. The difference to the classic expected utility theory is that investors have a higher utility decrease for losses compared to the utility increase for - in absolute terms - equivalent profits. In other words, losses hurt more than profits feel good. From an investor perspective, a losing stock is only a loss if it has been realized, i.e. the stock has been sold. Thus, investors might be reluctant to realize a loss but exit early profitable positions.

The second alternative explanation for the disposition effect is the misjudgment of probabilities by investors. Investors expecting losing stocks to outperform in the future might hold on to such stocks instead of selling them. On the other hand, they might expect winning stocks to perform poorly in the future and thus sell them early. Further evidence on the existence of the disposition effect has been provided by Weber (1998) by means of an experimental approach. He provided participants with probabilities for each outcome (increase vs. decrease of a stock) and thus argues that investors should not suffer from a probability misjudgment as a consequence. Therefore, he supports the first explanation of the disposition effect being an implication of prospect theory.[24]

Dhar and Ning (2006) analyze the disposition effect on an individual trader level based on a discount broker data set. Interestingly, they find that 19.7% of all investors do not have a significant disposition effect but rather show an opposite trading pattern. They distinguish investors by their wealth and occupation (professional vs. non-professional[25]) and find that wealthier and professional investors experience a lower disposition effect. Additionally, they provide evidence that trading frequency has a negative impact on the disposition effect indicating a learning effect of investors. Da Costa et al. (2013) find supporting evidence, showing that more experienced investors are less affected by the disposition effect. Besides articles discussed above, several similar studies exist, which analyze the disposition effect for other countries, such as Australia (Brown et al., 2006), China (Chen et al., 2007), Finland (Grinblatt and Keloharju, 2001), Israel (Shapira and Venezia, 2001), and Korea (Choe and Eom, 2009). Concluding, the disposition effect is a global phenomena that is very robust with respect to time and investor group.

Gambling Gao and Lin (2012) analyze stock trading as substitute to traditional lotteries. They find that trading volume of retail investors decreases in times of huge

[24] However, Kaustia (2010) argues that prospect theory is unlikely to explain the disposition effect. Barberis and Xiong (2009) support this statement. Based on a theoretical model, they find that prospect theory preferences do not necessarily result in a disposition effect but the reverse effect is a realistic outcome as well. Hens and Vlcek (2011) even provide theoretical evidence that investors would not even trade if they have prospect theory preferences. Nevertheless, ex-post, prospect theory can explain the disposition effect.

[25] The authors define professional occupation as working in professional/technical or managerial/administrative jobs. Non-professional occupation denote blue collar, white collar, or service jobs. See Dhar and Ning (2006) p.731 for more information.

jackpot sizes. In particular, this effect is visible for stocks with lottery-like characteristics, such as a high skewness of returns. On average retail investor trading volume reduces by 7.2% on days of huge lottery jackpot drawings. A similar study is conducted by Dorn et al. (2012) who are able to substantiate the findings of Gao and Lin for another market and with additional demographic data. In line with, among others, Albers and Hübl (1997), they provide evidence that especially male investors with a lower educational level are sensitive towards the substitution effect. However, they find no evidence for age and income to influence the substitution effect. They conclude with subtle irony that "if there were bigger jackpots more often, investors could allocate their portfolios to maximize expected returns in line with traditional economic theory, and seek their gambling thrills explicitly in the self contained arena of the lottery."[26]

3.3 Summary

In this chapter, I summarize findings for the behavior of issuers of structured products and retail investors in general. Several studies provide evidence that issuers quote higher prices for their products compared to theoretical fair values. Additionally, many studies find that issuers reduce their margins with shorter time to maturity, which is known as life cycle effect. However, direct evidence for investor anticipation and its impact on retail investor performance is scarce. Results on retail investor performance, their predictive power, and level of information do not provide a unified picture. Academic literature is strongly focusing on stocks as subject of investor trading, leaving only a very limited number of studies as a reference for retail investor trading in options or structured products.

Cognitive biases, such as overconfidence, sensation seeking, and limited attention have been discussed as influencing factors and trading motives of retail investor trading.

[26] Dorn et al. (2012), p. 26.

Chapter 4

Data and Methodology

THIS chapter gives detailed insights into my methodological approach and used data for all upcoming analyses. Section 4.1 presents characteristics for three different data sets and describes filters that have been applied to the data. Section 4.2 provides details and limitations of the pricing model used to replicate prices of product constituents.

4.1 Data Selection

Data used in this thesis is obtained from three distinct sources:

- quote data from Thomson Reuters DataScope Tick History (TRDTH),
- customer order flow and master data from Stuttgart Stock Exchange, and
- news data from Thomson Reuters.

This chapter comprises overall descriptions of those data sets, whereas used samples are described in detail within the individual chapters (see Section 5.3 and Section 6.3).

4.1.1 Thomson Reuters Quote Data

Continuously reported price updates are obtained from Thomson Reuters DataScope Tick History[1] archive through the Industry Research Centre of Asia Pacific (SIRCA).[2] TRDTH holds trade and quote data (TAQ) for "more than 45 million unique instruments across 400+ exchanges" timestamped up to miliseconds.[3] In this thesis, I use aggregated data as already provided by TRDTH. Data is either aggregated for fixed intraday periods, ranging from one second to one hour, or provided as End-of-Day (EOD) data. EOD data denotes official closing prices as reported by exchanges for individual instruments.[4] In particular, retrieved data includes Reuters Identification Code (RIC), opening price, closing price, best bid, best ask, highest price, lowest price, highest bid, highest ask, lowest bid, and lowest ask for each aggregation period. Appendix C shows examples for intraday and EOD data. Numerous other financial studies have used data from TRDTH.[5]

4.1.2 Stuttgart Stock Exchange Data

This data set comprises all customer orders submitted to Stuttgart Stock Exchange starting from April 1, 2009 until April 30, 2012.[6] Order flow data is not restricted to specific banks or brokers and, thus, enables drawing a representative picture of retail investor behavior. Additionally, I have access to master data describing individual characteristics of all structured products tradable at Stuttgart Stock Exchange. Table 4.1 shows one example for Stuttgart Stock Exchange master data.[7] Since this data set has not been available for research purposes before 2012 I describe the data set

[1] http://thomsonreuters.com/products_services/financial/financial_products/a-z/tick_history/.

[2] I thank SIRCA for providing access to Thomson Reuters DataScope Tick History archive. http://www.sirca.org.au/.

[3] Citation taken from http://thomsonreuters.com/products_services/financial/financial_products/a-z/tick_history/. Accessed on 04/04/2013.

[4] Focusing on EOD data, TRDTH is similar to the more well-known data source Thomson Reuters Datastream.

[5] Among others: Brown et al. (2012), Foley et al. (2012), Gong and Wright (2013), Hendershott and Riordan (2012), Riordan et al. (2013), Riordan and Storkenmaier (2012), Storkenmaier et al. (2012).

[6] I gratefully acknowledge data from Boerse Stuttgart, http://www.boerse-stuttgart.de/en.

[7] Depending on the type of the structured product, some variables might not be set.

in more detail.[8] Every product can be identified through the International Securities

TABLE 4.1: **Stuttgart Stock Exchange - Master Data Example.** This table shows one sample master data entry for the product "Side-Step-Zertifikat" with identification code "DE000CB7JQH1" issued by Commerzbank AG.

Variable	Value
Type	AZE
OptionType	Call
IssuerName	Commerzbank AG, Frankfurt am Main
WKN	CB7JQH
ISIN	DE000CB7JQH1
ExerciseType	e
Underlying	EU0009658145
StrikePrice	0
Currency	EUR
ExpirationDate	05.09.2011
SubscriptionRatio	1
ProductName	Side-Step-Zertifikat
FirstTradingDay	12.09.2007
LastTradingDay	02.09.2011
Description	Express-Zertifikate ermoeglichen eine vorzeitige Rueckzahlung zu einem festgelegten...
Cap	
SecurityLevel	2117.71
KnockOutBarrier	
InterestRate	
Rolling	n
PercentageQuotation	n
SecurityLevelValidFrom	12.09.2007
BonusLevel	
DateOfPayment	

Identification Number (ISIN), a unique identifier worldwide.[9] Master data allows for a detailed specification of an individual financial instrument. I use this data to duplicate payoffs of structured products. All variables as shown in Table 4.1 that are of relevance for a product should be contained in prospectuses of the issuer. To a smaller extent this information is also available on websites of brokers and exchanges.

[8] The following papers used data from Stuttgart Stock Exchange: Fritz and Meyer (2012), Meyer et al. (2013), Meyer et al. (2013), Schroff et al. (2012), Schroff et al. (2013).

[9] The Wertpapierkennnummer (WKN) is another identifier exclusively used in Germany.

A detailed description for shown master data variables is presented in Table D.1 in the appendix.

I exclude products from all future analyses if master data entries are not unique, i.e. if there a multiple entries with different attribute values. Additionally, I filter for products with rolling barriers, i.e. barriers that are not fixed throughout the life time of a product but instead frequently adjusted according to a specified formula developed by the issuer. Products with characteristics that are frequently adjusted usually have no fixed maturity and are often referred to as endless products. I exclude those products due to missing information about rolling dates and the method of attribute adjustments.

Table 4.2 shows a sample entry of Stuttgart Stock Exchange order flow data. A detailed description of all fields is presented in Table D.2. Every incoming order at

TABLE 4.2: **Stuttgart Stock Exchange - Order Flow Data Example.** This table shows one sample order data entry. Specifically, an order submission to sell 100 shares of DE000BN1U77 for at least EUR 4.69.

Variable	Value
Ordernumber	805024200286
Timestamp	2009-05-02 05:09:07.830
Code	001
ISIN	DE000BN1U77
Buysell	V
Size	100.00
Limit	4.6900
Tradeprice	
Tradequantity	
RoutingID	xxxx

Stuttgart Stock Exchange is given a unique number, which allows for tracking status changes of orders. An order evolves through several states, which are identified through the *Code* variable. The most important codes are: 001 (submission), 003 (modification of order limit or size), 005 (cancellation), and 011 (execution). This means that I observe at least two order flow entries for a submitted and executed order.[10] Every status change is timestamped up to milliseconds and, thus, makes it possible

[10]In case of partial executions there are order flow entries in the amount of partial executions.

to calculate differences in time between each status. Compared to other more well-known data sources such as TRDTH, this data set bears the advantage of faultless identification of a buy or sell order. Therefore, I am not depending on measures to identify trade directions such as Lee and Ready (1991), which results in a higher accuracy since I do not have to deal with orders that have been subject of a flawed identification. Through the additional information of submitted orders, the data set distinguishes between originally submitted limit price and size, and price and size at execution. Investors submitting a market order would set a limit price, which allows for immediate execution of the order.[11] Unfortunately, trade direction is only provided for order flow entries at submission. Due to a fixed overall period of data availability, some orders exist that have been executed within my sample periods, but which have been submitted to the exchange outside of my overall data period. Therefore, I exclude executed orders from respective samples if there are no submission information. Additionally, I have access to routing information of orders, revealing a bank, broker, or routing provider. Not all banks have a direct access to Stuttgart Stock Exchange, which leaves them with routing orders of their customers via other institutions that are directly connected to the exchange. Due to data protection policies, this information is not disclosed in this thesis.

4.1.3 Thomson Reuters News Data

I analyze retail investor behavior with respect to news events. I have access to archived newswire messages distributed through Thomson Reuters. Newswire messages are available in real-time and as historical data. Real-time news data is increasingly used by HFT to trade immediately on changes in fundamentals or market movements. Historical data can be used for quantitative analyses and to test trading systems of algorithmic traders. The commercial real-time product to obtain newswire messages is called Thomson Reuters NewsScope Real-time. Reuters "deliver[s] over 500,000 alerts and over two million unique stories a year."[12] According to Reuters, their newswire messages are distributed to more than "370,000 financial and media

[11] Due to the structure of the data, I use within this thesis the expressions *market order* and *marketable order* simultaneously.

[12] `http://thomsonreuters.com/products_services/financial/financial_products/a-z/newsscope_application_license/`. Accessed 04/04/2013.

professionals worldwide".[13]

Thomson Reuters NewsScope Sentiment Engine (RNSE) provides additional linguistic services, which process newswire messages and enrich them with additional information. This service is now known as Thomson Reuters News Analytics (TRNA).[14] As a consequence, generated information is readable by computer-algorithms and, thus, allows for sophisticated trading strategies. RNSE analyzes newswire message along three dimensions: relevance, sentiment, and novelty. Relevance is a numeric value between zero and one and captures the relevance of a news message for a referred stock. Sentiment is a metric identifying the tone of a news message for a referred stock. It is either positive (1), negative (-1), or neutral (0). Novelty identifies whether there have been news messages with a similar content before. If the content of a news message refers to more than one stock, a separate news message is generated for each stock including the same message content but different values for those three measures. Thus, a news message referring to the regulation of the telecommunications networks might be negative for Deutsche Telekom, but positive for its competitors.

My news data set is already enriched through RNSE. Table 4.3 shows one sample news message. Table E.1 shows a more detailed description of relevant fields. Each news message is tagged with a Primary News Access Code (PNAC), which allows for the identification of a developing story across multiple news messages. I keep the first entry of every news message group with the same PNAC and delete the rest to ensure a certain novelty of the news messages.

RNSE news have been used in several financial studies.[15] Groß-Klußmann and Hautsch (2011) analyze RNSE news and find that "news engines are able to successfully structure and categorize the intraday news flow".[16] Additionally, they find significant influences of intraday news on trading volume and market volatility.

[13] `http://thomsonreuters.com/content/financial/pdf/enterprise/NewsScopeBrochure.pdf`. Accessed 04/04/2013.

[14] Since news data were originally derived from RNSE, I refer to my news data source still as RNSE instead of TRNA. `http://thomsonreuters.com/products_services/financial/financial_products/a-z/news_analytics/`.

[15] Among others: Dzielinski (2011), Groß-Klußmann and Hautsch (2011), Leinweber and Sisk (2011a), Leinweber and Sisk (2011b), Riordan et al. (2013), Storkenmaier et al. (2012), Dzielinski (2012), Zhang (2012), Dzielinski and Hasseltoft (2013).

[16] Groß-Klußmann and Hautsch (2011), p. 336.

TABLE 4.3: **RNSE Data Sample.** This table shows a sample news message for E.ON SE.

Variable	Value
timestamp	16 JUL 2009 13:37:29.292
bcast_ref	EONGn.DE
stock_ric	EONGn.DE
item_id	2009-07-16_13.37.29.nBEB002433.A1.43834e3a
relevance	1
sentiment	1
sent_pos	0.844345
sent_neut	0.00642559
sent_neg	0.0341205
lnkd_cnt1	0
lnkd_cnt2	0
lnkd_cnt3	0
lnkd_cnt4	0
lnkd_cnt5	0
lnkd_id1	.
lnkd_id2	.
lnkd_id3	.
lnkd_id4	.
lnkd_id5	.
lnkd_idpv1	.
lnkd_idpv2	.
lnkd_idpv3	.
lnkd_idpv4	.
lnkd_idpv5	.
item_type	ALERT
item_genre	NOT DEFINED
bcast_text	MERKEL SAYS RUSSIA AND GERMANY DOING ALL WE CAN TO GET NECESSARY APPROVAL FOR NORD STREAM PIPELINE
dsply_name	1
pnac	nBEB002433
story_type	S
cross_ref	.
proc_date	16JUL09:00:00:00
take_time	13:37:29
story_date	16JUL09:00:00:00
story_time	13:37:29
named_item	.
take_seqno	1
attribtn	RTRS
prod_code	0 ELE E G
topic_code	DE WEU EUROPE RU EMRG POL DIP NGS TRD CEEU TR TM AZ LNG LEN RTRS
lang_ind	EN

4.2 Pricing Model

In this section, I present details about the asset pricing model used to calculate theoretical prices for structured products in this thesis. First, I introduce analytic formulas to derive product prices and, second, I discuss the calculation of model parameters. Section 4.2.4 discusses limitations of my approach compared to other existing models.

4.2.1 (Practitioners) Black-Scholes Model

Option pricing bears a general model risk, which makes it impossible to find perfect fair values. As a consequence my analysis faces two kinds of model selection risk. First, I have to select a model I believe to serve best for this sort of valuation. Second, the model that has been selected by the issuing bank, which is not publicly known, but has influence on my results. Even if I knew which models are used, it is still uncertain how banks implement a model. In this case the calibration of the underlying volatility is of particular interest. In this thesis, I use an adapted version of the Black and Scholes (1973) model, which is known as Practitioners Black-Scholes model (PBS).

I use the following notations: Let K be the strike price, S_t the underlying price at time t, q the continuous dividend yield, σ the volatility of the underlying asset, and r denotes the (continuous) risk-free interest rate. $N(\cdot)$ denotes the cumulative normal distribution function. Within the Black-Scholes model the price of the underlying asset is assumed to follow a geometric Brownian motion:

$$\frac{dS_t}{S_t} = \mu dt + \sigma dW_t, \tag{4.1}$$

where μ denotes the annual expected return on the underlying stock and W_t is a standard Wiener process. The following formulas for European calls $C_t^E(K)$ and puts $P_t^E(K)$ with strike K at time t and time to maturity T are obtained from Hull (2005):

$$C_t^E(K) = S_t e^{-qT} N(d_1) - K e^{-rT} N(d_2), \tag{4.2}$$

$$P_t^E(K) = Ke^{-rT}N(-d_2) - S_t e^{-qT}N(-d_1) \tag{4.3}$$

with d_1 and d_2 being defined as

$$\begin{aligned} d_1 &= \frac{\ln(\frac{S_t}{K}) + (r - q + \frac{\sigma^2}{2})T}{\sigma\sqrt{T}}, \\ d_2 &= d_1 - \sigma\sqrt{T}. \end{aligned} \tag{4.4}$$

In the following, I present pricing formulas for structured product types that are covered in my thesis.

Discount Certificate

A discount certificate (see Section 2.3) wraps up a zero-strike call and the sale of a call option. As the name suggests, the zero-strike call is an European call option with strike price zero. Basically, the zero-strike call accounts for the valuation of potential dividend payments and, thus, is equivalent to a long position if there are no dividend payments at all. The strike price of the call option is the cap of the discount certificate. Let DC_t be the price of a discount certificate at time t and κ denotes the cap level. The price of a discount certificate can then be calculated as follows:

$$DC_t = C_t^E(0) - C_t^E(\kappa). \tag{4.5}$$

In order to value the zero-strike call, very small strike values in the call price formula (4.2) can be used or it just equals S_t in case there are no dividend payments at all.

Knock-out Warrant

The knock-out call (put) warrant (see Section 2.3) can be duplicated by a down-and-out call (up-and-out put) option (Rubinstein and Reiner, 1991). Both options are knock-out options and belong to the category of barrier options. Barrier options either cease to exist or start to exist if a certain barrier level is touched during the life time of that option. For example, a down-and-out call option is a regular call option that ceases to exist if the underlying asset touches a defined lower barrier level. To calculate prices of those barrier options, I use the standard Black-Scholes valuation extended to dividend payments and barrier characteristics, which was introduced by Merton (1973). Let H be the barrier level of the barrier option; let $C_t^{DI}(K,H)$ ($C_t^{DO}(K,H)$) be the price of a down-and-in (-out) call option, and $P_t^{UI}(K,H)$ ($P_t^{UO}(K,H)$) the price of a up-and-in (-out) put option given strike K and barrier H. The price of a knock-out call warrant ($C_t^{DO}(K,H)$) can then be calculated as follows. If the barrier is less than or equal to the strike price the value of a down-and-in call and a down-and-out call are given by

$$\begin{aligned} C_t^{DI}(K,H) &= S_t e^{-qT}\left(\frac{H}{S_t}\right)^{2\lambda} N(y) - Ke^{-rT}\left(\frac{H}{S_t}\right)^{2\lambda-2} N(y-\sigma\sqrt{T}), \\ C_t^{DO}(K,H) &= C_t^{E}(K) - C_t^{DI}(K,H) \end{aligned} \tag{4.6}$$

where

$$\begin{aligned} \lambda &= \frac{r-q+\frac{\sigma^2}{2}}{\sigma^2}, \\ y &= \frac{\ln(\frac{H^2}{S_t K})}{\sigma\sqrt{T}} + \lambda\sigma\sqrt{T}. \end{aligned} \tag{4.7}$$

If the barrier is greater than or equal to the strike price the values are given by

$$\begin{aligned} C_t^{DO}(K,H) &= S_t N(x_1) e^{-qT} - Ke^{-rT} N(x_1-\sigma\sqrt{T}) \\ &\quad - S_t e^{-qT}\left(\frac{H}{S_t}\right)^{2\lambda} N(y_1) + Ke^{-rT}\left(\frac{H}{S_t}\right)^{2\lambda-2} N(y_1-\sigma\sqrt{T}), \\ C_t^{DI}(K,H) &= C_t^{E}(K) - C_t^{DO}(K,H) \end{aligned} \tag{4.8}$$

with

$$\begin{aligned} x_1 &= \frac{\ln(S_t/H)}{\sigma\sqrt{T}} + \lambda\sigma\sqrt{T}, \\ y_1 &= \frac{\ln(H/S_t)}{\sigma\sqrt{T}} + \lambda\sigma\sqrt{T}\,. \end{aligned} \tag{4.9}$$

Similarly, prices for a knock-out put warrant ($P_t^{UO}(K,H)$) with $H \geq K$ are obtained by

$$(4.10)\qquad \begin{aligned} P_t^{UI}(K,H) &= -S_t e^{-qT}\left(\frac{H}{S_t}\right)^{2\lambda} N(-y) + Ke^{-rT}\left(\frac{H}{S_t}\right)^{2\lambda-2} N(-y+\sigma\sqrt{T}),\\ P_t^{UO}(K,H) &= P_t^E(K) - P_t^{UI}(K,H). \end{aligned}$$

If $H \leq K$ then

$$(4.11)\qquad \begin{aligned} P_t^{UO}(K,H) &= -S_t N(-x_1)e^{-qT} + Ke^{-rT}N(-x_1+\sigma\sqrt{T})\\ &\quad + S_t e^{-qT}\left(\frac{H}{S_t}\right)^{2\lambda} N(-y_1) - Ke^{-rT}\left(\frac{H}{S_t}\right)^{2\lambda-2} N(-y_1+\sigma T),\\ P_t^{UI}(K,H) &= P_t^E(K) - P_t^{UO}(K,H). \end{aligned}$$

Note that the barrier option formulas do only hold under the condition that the option has not been knocked out yet; else the price is zero. In addition, this valuation approach assumes the price of the underlying asset to be monitored continuously.

(Classic) Bonus Certificate

To value a bonus certificate I have to determine the price of an European zero-strike call and a down-and-out put option. Let T^* be the maturity date and $P_t^{DO}(K,H)$ the price of the down-and-out put option at time t on the designated underlying. Then the price BC_t of a bonus certificate at time $t \leq T^*$ is given by

$$(4.12)\qquad BC_t = C_t^E(0) + P_t^{DO}(K,H)$$

where the down-out-put option has the same characteristics as the bonus certificate, i.e. the strike price is equal to the bonus level and the barrier matches the security level. The value of a down-and-out put option is equal to a regular put minus the

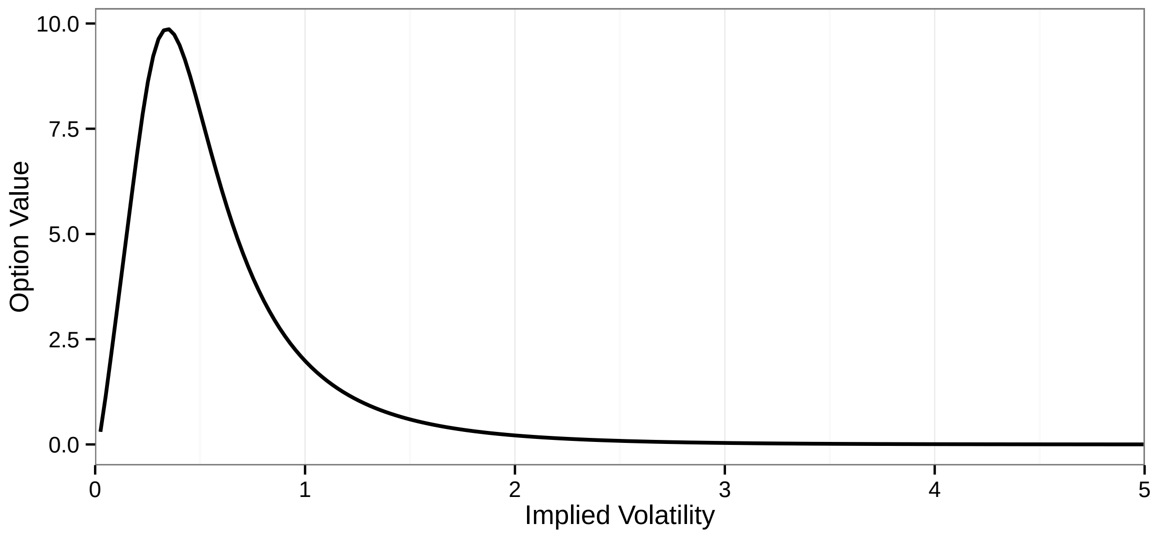

FIGURE 4.1: **Black-Scholes Value of a Down-and-out Put Option.** The x-axis shows the implied volatility, whereas the y-axis shows Black-Scholes model values for a down-and-out put option with strike $K = 100$, barrier $H = 50$, underlying asset price $S = 100$, risk-free interest rate $r = 0.02$, time to maturity $T = 1$, and dividend yield $q = 0$.

value of down-and-in put option:

$$
\begin{aligned}
P_t^{DI}(K,H) &= -S_t N(-x_1)e^{qT} + Ke^{-rT}N(-x_1 + \sigma\sqrt{T}) \\
&\quad + S_0 e^{-qT}\left(\frac{H}{S_t}\right)^{2\lambda}[N(y) - N(y_1)] \\
&\quad - Ke^{-rT}\left(\frac{H}{S_t}\right)^{2\lambda-2}[N(y-\sigma\sqrt{T}) - N(y_1 - \sigma\sqrt{T})], \\
P_t^{DO}(K,H) &= P_t^E(K) - P_t^{DI}(K,H)
\end{aligned}
\tag{4.13}
$$

where λ, x_1, y_1, and y are defined as before. Figure 4.1 shows an example for a down-and-out put option. For the context of this thesis, it is important to mention that, in contrast to plain vanilla options, an increase in volatility does not necessarily result in an increase of the value of the down-and-out put option. In fact, close to the barrier, an increase in volatility results in a substantially lower option value.

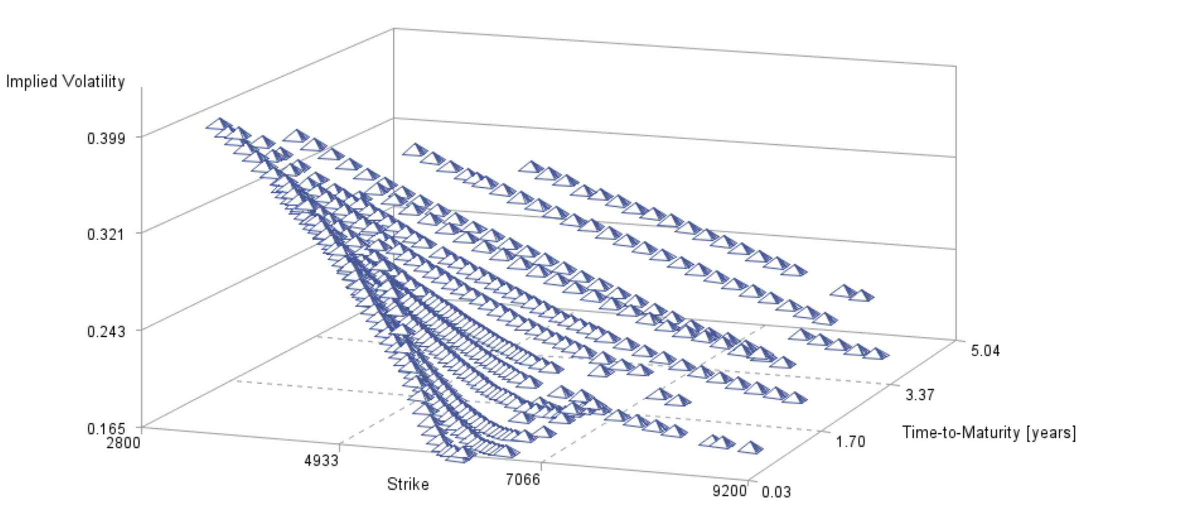

FIGURE 4.2: **Implied Volatility Skew.** The x-axis shows the strike, the y-axis shows implied volatility parameters, and the z-axis shows the time to maturity for all DAX options traded at EUREX on 01/07/2010 10:00 a.m.

Capped Bonus Certificate

The result of combining classic bonus certificates with a maximum payoff results in capped bonus certificates. In addition to buying a zero-strike call and a down-and-out put option, the investor sells passively a call option with the cap level equal to the strike price when buying a capped bonus certificate. The price CBC_t of a capped bonus certificate is then calculated in the following way:

$$CBC_t = C_t^E(0) + P_t^{DO}(K,H) - C_t^E(\kappa). \tag{4.14}$$

4.2.2 Black-Scholes and the Volatility Smile/Skew

The model developed by Black, Scholes, and Merton has been a quantum leap in option pricing. The classic Black-Scholes model has been criticized ever since its original formulation, and it is well known that it does not perform very well in capturing actual option prices. Originally, the volatility parameter is based on the past return series of the underlying asset. One major assumption of the model is that it assumes volatility to be constant across options with different strikes and the same time to maturity. However, as shown in Figure 4.2, this assumption does not hold true in practice. Figure 4.2 visualizes a snapshot for implied volatility parameters for DAX options with different strikes and time to maturities on January 7, 2010 at 10:00 a.m. Implied volatilities are higher for options with lower strikes. For a fixed time to maturity, this pattern is known as volatility smile or skew due to its U-shape and it is a distinctive feature for index and equity options. The smile/skew is more pronounced for options with shorter time-to-maturity. This pattern has first been observed after the stock market crash in 1987, which leads to the common assumption that the volatility smile/skew is the result of the fear of another crash in the future ("crash-o-phobia") (cf. Rubinstein, 1994). Other explanations for the smile are influences of liquidity and transaction costs (Peña et al., 1999). Basically, the observed volatility smile/skew implies that out-of-the-money puts are priced considerably higher than out-of-the-money calls. To overcome this drawback in the Black-Scholes model, I assume the volatility parameter to be a non-constant function of time to maturity and strike. This modification of the original model is referred to as Practitioners Black-Scholes.[17] The volatility parameter used as input parameter in the PBS model is therefore implicitly calculated from existing options through solving the Black-Scholes formula for σ. Hence, I rather must have set $\sigma = \sigma(K, T)$ in the above formulas for the calculation of different product prices.

Due to institutional conventions, a limited number of strikes and expiry dates are traded. Hence, implied volatility can only be derived pointwise. Even though implied volatility observations are gathered in this pointwise design, practitioners think of them as stemming from a smooth and well-behaved surface. This requires suitably chosen intrapolation and extrapolation techniques or a fully specified model for the implied volatility surface. Figure 4.3 shows a possible volatility surface for the afore visualized option data snapshot. The following subsection outlines the implied volatility estimation method used in this thesis.

4.2.3 Implied Volatility Estimation

I adjust the implied volatility parameter for each observation for each product independently. To estimate the volatility parameter of the underlying asset, I extract

[17] Very similar versions of the model are known as ad-hoc Black-Scholes model (Berkowitz, 2010) or Implied Volatility Function model (Hull and Suo, 2002).

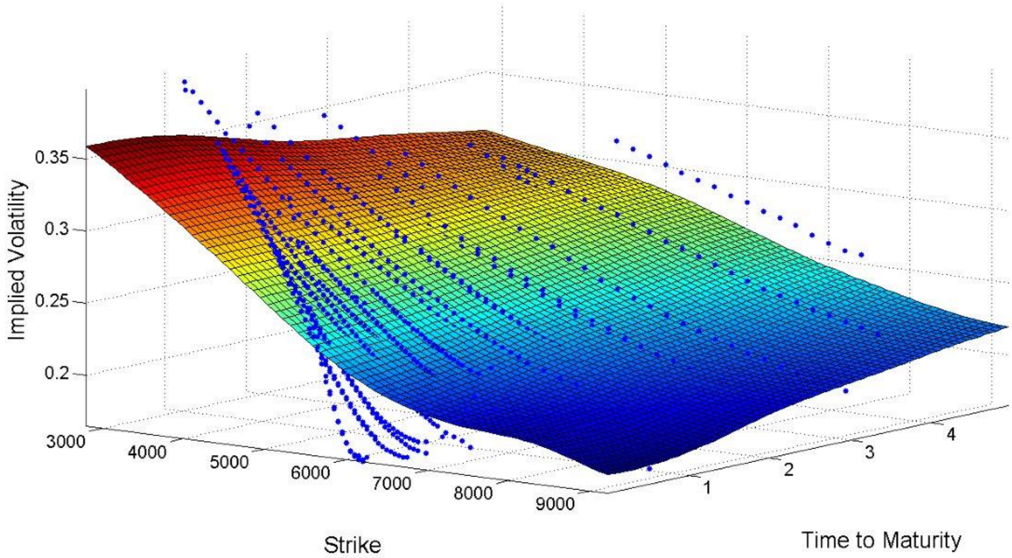

FIGURE 4.3: **Implied Volatility Surface.** The x-axis shows the strike, the y-axis shows implied volatility parameter, and the z-axis shows the time to maturity for all DAX options traded at EUREX on 01/07/2010 10:00 a.m.

the implied volatility from options traded at EUREX based on time to maturity and strike by inverting the standard Black-Scholes formula for calls and puts, respectively. I obtain all call and put options traded at EUREX for all relevant underlying assets within individual sample periods from SIRCA and compute the individual implied volatility. Figure 4.4 shows the daily average implied volatility of EUREX options with the DAX index as underlying throughout 2010. The implied volatility increased substantially in May 2010 compared to the beginning of the year. One explanation could be the flash crash on May 6, 2010 when the Dow Jones index lost and regained approximately 1000 points within a few minutes.[18]

Instead of using an averaging procedure, the PBS model incorporates volatility as a function of time to maturity and strike. Dumas et al. (1998) investigate several parameterizations and find all of them to outperform a constant volatility factor. I use the volatility function

$$\sigma(K,T^*) = \alpha + \beta_1 K + \beta_2 K^2 + \epsilon, \tag{4.15}$$

[18]For more information on the flash crash see, for example, Kirilenko et al. (2011).

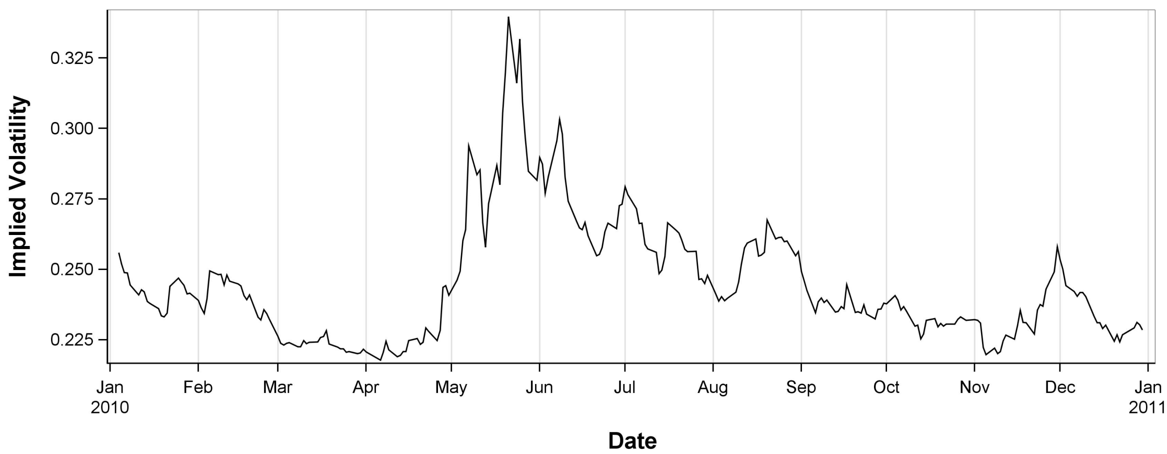

FIGURE 4.4: **Implied Volatility Over Time.** The x-axis shows the date, whereas the y-axis shows the daily average implied volatility across all DAX options traded at EUREX.

where T^* indicates the maturity of the EUREX option chains used to estimate the parameters by Ordinary Least Squares. Exact matches of the time to maturity of structured products, more precisely the incorporated (barrier) options, with options traded at EUREX are rather rare. Accordingly, for those options where I do not have an actual fit, I use those two option chains having the closest maturity dates, from above and below respectively, compared to the maturity date of the structured product. An option chain denotes a collection of put and call options on the relevant underlying beyond a wide range of strike prices but with same maturity[19]. As a result, I obtain for the strike of the structured product two volatility parameter through (4.15) for the different option chains.[20] Finally, to determine the implied volatility estimate for each observation with respect to the time to maturity, I weight both volatility estimates according to the difference in time between maturity dates of the option chains and the structured product. Applying the relevant volatility parameter[21] for the individual formula eventually results in the 'fair' theoretical price of the analyzed product.

[19]cf. EUREX website for details, www.eurexchange.com/.

[20]I note that in case of barrier options it is theoretically debatable whether to apply the strike level, the barrier level, or anything in between into the implied volatility function. I test strike level, barrier level, as well as the average of both and find that the barrier level returns the best results in terms of standard and maximum deviation from observed prices.

[21]Additionally, I calculate prices using historical moving-average volatilities with horizons of up to 100 days instead of the implied volatility interpolation procedure. I obtain price differences similar to those reported.

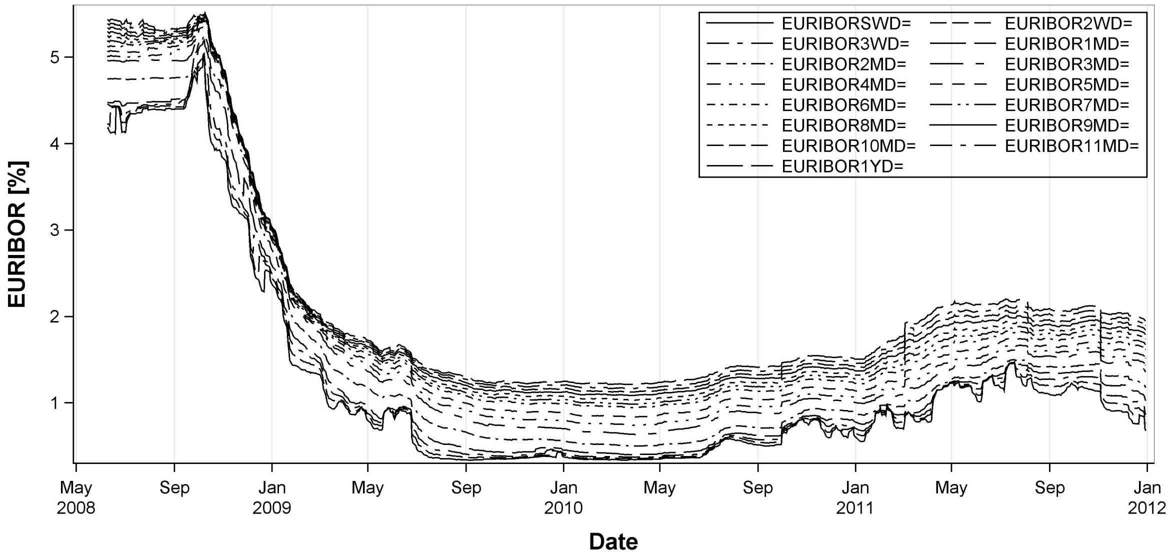

FIGURE 4.5: **Euro Interbank Offered Rate Over Time.** The x-axis shows the date, whereas the y-axis shows the daily last EURIBOR distinguished by periods of 1 to 3 weeks and 1 to 12 months.

For the valuation of bonus certificates in Chapter 5 the implied volatility calculations are realized on a 5 min basis. Prices for discount certificates and capped bonus certificates are based on EOD option data.

For the risk free interest rate, I use Euro Interbank Offered Rate (EURIBOR) for periods of 1 to 3 weeks and 1 to 12 months, and 2 year and 3 year yields of the REXP Bond index.[22] Figure 4.5 shows the EURIBOR from May 2008 until January 2011. In 2010, the sample period for later analyses, the EURIBOR has considerably decreased compared to years before. For maturity dates that do not correspond to the exact periods of EURIBOR and REXP rates, I interpolate between the closest two rates available. For example, the desired interest rate for a period of 1,5 weeks is computed by equally weighting the one and two week EURIBOR rate.

[22]ISIN DE0008469115. REXP Bond Yields are the yields of a synthetic bond containing 30 German government bonds and are reported on a daily basis by Deutsche Boerse.

4.2.4 Limitations

I believe that the PBS model approach serves best for my analysis. Dumas et al. (1998) investigate the model error of several different deterministic volatility functions in the Black-Scholes model compared to observed prices for S&P 500 index options. All proposed volatility functions provide better results in terms of mean squared valuation errors than the original Black-Scholes model assuming constant volatility. Hull (2005) and Christoffersen and Jacobs (2004) confirm these findings for European and compound options and show that for this class of options the PBS model provides better results — again with respect to the mean squared errors of model and observed option prices — than a stochastic volatility approach like the Heston (1993) model. I assume that my implied volatility estimation performs even better due to a larger option data set than in those cited studies. Singh et al. (2011) support the effectiveness of the PBS model compared to the standard Black-Scholes model and the Heston and Nandi (2000) GARCH model. In case of exotic options, particularly path-dependent options, the PBS approach has some disadvantages compared to structural stochastic volatility models but still improves the standard Black-Scholes model (cf. Hull, 2005). Indeed, Christoffersen and Jacobs (2004) state that PBS is by no means superior to structural models but is useful as a benchmark. However, An and Suo (2009) examine the accuracy of hedging strategies for exotic options based on several models: PBS, constant elasticity of variance model, stochastic volatility model, and the jump diffusion model. All models are recalibrated whenever they are used to study them in a practitioners-like way. They find that the PBS model performs better than alternative models for barrier options as long as it is frequently recalibrated. However, the performance is strongly depending on the degree of path dependency as also pointed out by Hull and Suo (2002).

The purpose of my analyses in this thesis is not to improve option pricing theory, but in getting an intuition about the systematical (average) premium behavior of structured products. Hence, the PBS approach seems to be the best choice to achieve a reliable market estimation of fair prices. For a comprehensive discussion of the PBS approach see Berkowitz (2010).

From a practitioners point of view, I emphasize the performance aspect of a pricing model. It has to be considered that investment banks have to provide binding quotes and liquidity in real time[23] for up to 100,000 different structured products, something that cannot be accomplished with sophisticated complex mathematical approaches, such as jump diffusion models. Therefore it is more likely that issuing banks employ quick to calculate formulas or heuristics to provide continuous quotes and use sophisticated structural models to control hedging and risk of their product portfolio.[24]

Summarizing, I am aware that there is a potential model (selection) risk for my analyses, but from the above argumentation, robustness checks, and related empirical studies (e.g. Baule and Tallau, 2011) I conclude that the overall influence on the average (overpricing) premiums is negligible. I also remark that my analyses treat each product isolated, i.e. independent of a bank's other issued products. Consequently, I do not account for possible synergistic effects of a large product portfolio.

4.3 Summary

In this section, I described data sources and methodological approaches that are used in this thesis. I use quote, trade, and news data from three distinct sources to run in-depth analyses on the market of structured products. Data from Stuttgart Stock Exchange makes my analyses a valuable addition to the common literature, since this data set represents the majority of exchange-traded transactions in structured products and thus allows me to sketch a representative picture across brokers for the entire retail investor population.[25]

In order to derive theoretical prices for different product types I rely on the Practitioners Black-Scholes model, a variation of the standard Black-Scholes model including a more sophisticated (implied) volatility parameter. By the use of this adapted model I try to overcome some of the drawbacks of the classic model. In the following chapter, I use the discussed method and data to analyze the pricing of structured products by issuers.

[23]Issuers usually provide quotes several times per second depending on the current market situation.
[24]For example, see Haug and Taleb (2011) for details about the use of heuristics by option traders.
[25]See `http://www.derivateverband.de/DEU/Statistiken/Boersenumsaetze` (accessed 10/08/2013) for detailed statistics regarding stock exchange turnover for structured products in Germany.

Chapter 5

Investment Banks' Price-Setting Behavior

"Pricing is actually a pretty simple and straight forward thing. Customers will not pay literally a penny more than the true value of the product."

Ron Johnson (Former Vice President at Apple Inc.)

5.1 Introduction

FINANCIAL institutions sell products to retail investors that mimic payoffs of complex investment strategies. The universe of such investment products is increasing constantly; in 2013 more than one million structured products were tradable in Germany.[1] This market is unique in the sense that issuing banks act as the main liquidity supplier and investors' primary trading counterpart. I study the intraday and interday pricing policy of issuers for structured investment products. I decompose quoted product prices into two general parts: (1) the theoretical fair value; and (2) the product premium. I analyze two different factors behind changes in premium: hedging costs and anticipation of investor demand. Investment banks hedge themselves

[1] See Section 2.3 for descriptive statistics on the German and other European markets.

continuously throughout the day, suggesting that hedging costs and premiums are highly correlated. In addition investment banks may anticipate the demand for their products and adjust prices to capture rents.

I focus on bonus certificates as one major group of traded structured investment products[2]. Bonus certificates are derivatives, which provide investors with a complex payoff structure at maturity, which is designed to reduce the risk compared to a direct investment in the underlying instrument. Investors receive a minimum payment in the amount of the bonus level if the underlying never touched a predefined barrier.

Due to the apparent safety of bonus certificates, bank advisers frequently offer these products to their customers despite the hardly understandable price development, and nontransparent inner costs. From a legal perspective, bonus certificates are designed as bearer bonds, which permits only the issuing bank as counter party at date of maturity, adding a default risk for the investor. During maturity, the issuing bank acts as the major liquidity supplier allowing only limited price competition.

A bonus certificate is a synthetic product, whose constituent parts can not be traded at common derivative exchanges, which prohibits intuitive price comparison for retail investors. It consists of a zero-strike call and a down-and-out put barrier option. The latter increases the price-setting complexity through its path dependency. I obtain theoretical prices using an adopted version of the Black and Scholes (1973) modeling approach.[3] I measure effects of both, intraday and interday, shifting premiums on the wealth of retail investors, which is defined on a loss per trade basis.

Structured products have been subject of several studies for the last years. Generally, studies have focused on the overpricing (including a premium) of products on a daily basis and the life cycle effect, which denotes the decrease of overpricing with shorter maturity. For a comprehensive overview of this literature refer to Section 3.1.

This thesis contributes to the literature by providing evidence for the price-setting behavior of investment banks for one of the most important product types for German retail investors. Analyzing the intraday as well as the interday pricing of issuers

[2]Bonus certificates made up for ca. 13% of order book volume in June 2012 at German derivative exchanges (Source: DDV).

[3]See Section 4.2 for more details on the pricing model.

makes it a valuable addition to existing literature. Due to a unique data set provided by the Stuttgart Stock Exchange and continuous intraday quotes of issuers I am able to measure precisely the effect of order anticipation of investment banks. My sample includes all trades at Stuttgart Stock Exchange and provides an ideal basis to measure resulting effects of the price-setting behavior on the wealth of retail investors.[4]

I find that investment banks quote prices above theoretical fair prices and increase their premiums towards the end of the day. Furthermore, I find support for the life cycle hypothesis for bonus certificates. I find that investment banks increase premiums in times of high uncertainty. Additionally, investment banks react to the demand of their products by reducing or increasing premiums depending on the type of trade. They reduce premiums after a sell order, and they increase them after a buy order. I provide evidence that retail investors are affected by intraday and interday shifts in premium and that they lose approximately 1% on average of their invested capital due to those shifts.

In extension to those results, I examine briefly premiums of products that are less and more complex compared to bonus certificates. I find substantially lower premiums for less complex products (discount certificates), and higher premiums for more complex products (capped bonus certificates). Additionally, I analyze the comparability of structured products across issuers. I find that less than 1% of all products have an identical substitute from another issuer and thus allow for a direct price comparison.

The remainder of this chapter is organized as follows: Section 5.2 derives research questions addressed in this chapter. I describe my sample in Section 5.3. I identify and analyze possible premium influences in Section 5.4 and Section 5.5 concludes.

5.2 Research Questions

This chapter addresses in particular Research Question 1, as mentioned below.

Research Question 1. *Do issuers exploit the ignorance of retail investors?*

[4]See Section 4.1 for more details on the data.

In order to identify a potential exploitation, I break this question down into several sub questions focusing on this scenario from different perspectives. Generally, observed higher prices for products relative to their theoretical values result in a greater financial leeway for issuers, since they have more money at hand than they actually need to build the product. Therefore, as a first step, I study the discrepancies between quoted and theoretical prices:

> **Research Question 1a.** *What is the average premium issuers include in their products?*

Most structured products have a fixed time to maturity. Depending on the product type it varies between a few months and several years. Assuming that more buy than sell orders exist in the first period of a product's life time and vice versa towards the end, a continuous decrease of the premium until maturity resembles the gain of almost risk-free profits for issuers. Research Question 1b captures this scenario:

> **Research Question 1b.** *How do premiums change over the life time of structured products?*

In addition to the analysis of this overall time influence on the premium of structured products, I also examine whether premiums change during the day. Regardless of a continuous decrease of premiums over the life time, issuers might use similar patterns during the day to anticipate investor behavior.

> **Research Question 1c.** *How do premiums change during the day?*

Fortunately, I have retail trading data at my disposal, which allows me to deepen the previous analyses by examining the direct effects of executed orders on the premium. The following research question addresses the consideration that issuers change their premiums depending on the current net volume.

> **Research Question 1d.** *Are issuers anticipating retail investor demand?*

Additionally, I study whether changes in premium have any effect on retail investor wealth. More precisely, I do not study the effect of market timing but the change of premiums between buy and sell decisions of investors. This objective is reflected in the following research question.

> **Research Question 1e.** *What is the impact of premium changes on wealth of investors?*

Finally, I examine whether premiums and competition differ between overall product types of different complexity, i.e. products that incorporate a more or less complex option structure.

Research Question 1f. *What is the effect of complexity on premiums and competition of issuers?*

The following section gives insights into my sample, which is used to answer the research questions above.

5.3 Sample Selection and Descriptive Statistics

I analyze the price-setting behavior of investment banks for one of the most important retail investor product types: (classic) bonus certificates. As underlying I focus on the German performance index DAX. My sample consists of all trading days between January 4th, 2010 and December 31st, 2010, which results in 255 days. I obtain intraday quote data on a 5 min basis for bonus certificates tradable at Stuttgart Stock Exchange as well as for the DAX and XDAX from Thomson Reuters DataScope Tick History archive through SIRCA. The XDAX is an indicator for the DAX index outside regular trading hours of the DAX. It is based on DAX futures traded at Eurex. Analogously, I obtain Eurex option data (so-called option chains) for all strikes and maturities, which are used to calibrate my pricing model, i.e. my implied volatility parameter. On average, there are about 760 different options available on each day during my sample period. I obtain full master data and customer trade data for all structured investment products from Stuttgart Stock Exchange.[5] I only take products into account which have at least a trading volume, which adds up to EUR 10,000 over their life time.

Table 5.1 reports descriptive statistics for my trade data set. I remove all bonus certificates for which no intraday data can be obtained through SIRCA. My sample comprises of 4,161 trades, consisting of 4,161 buy orders and 2,776 sell orders, with a total volume of approximately EUR 250 million. The average trade size is EUR 60,302. However, the median trade size (EUR 13,479) is substantially smaller. Figure

[5] Refer to Section 4.1 for more information on the different data sets. A detailed description of all available fields of the Stuttgart Stock Exchange data is presented in Appendix D.

TABLE 5.1: **Descriptive Statistics - Trades.** This table captures descriptive statistics for the trade data sample obtained from Stuttgart Stock Exchange. It consists of 255 trading days between January 4th, 2010 and December 31st, 2010.

	Total
Total Volume [EUR]	250,918,523
Trade Count	4,161
Number of Buys	2,776
Number of Sells	1,385
Average Trade Size [EUR]	60,302.46
Trade Size Std. Dev.	(243,014)
Median Trade Size [EUR]	13,479.01

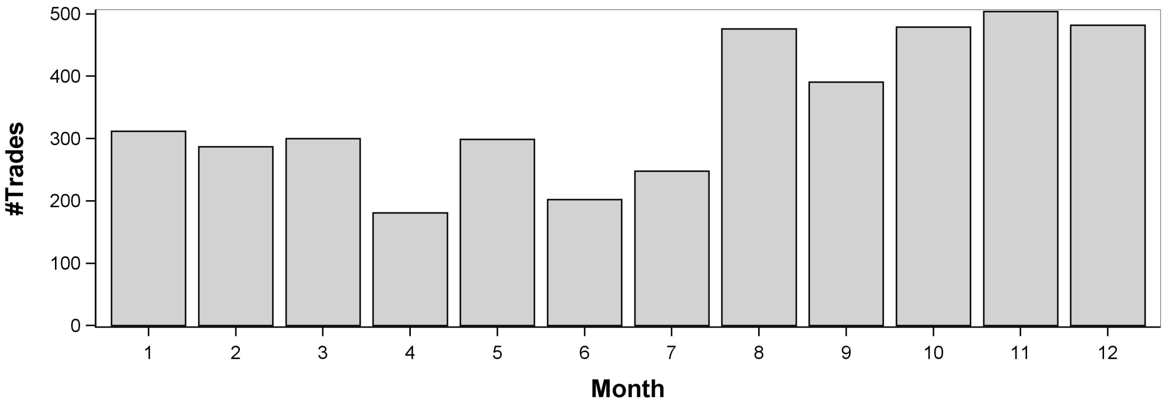

FIGURE 5.1: **Number of Trades Throughout 2010.** This figure visualizes the number of trades per month for the sample period.

5.1 shows the number of trades per month throughout the sample period. The number of trades increased considerably towards the end of the year. This effect could be driven by tax considerations of investors (see, e.g., Barber and Odean, 2004; Grinblatt and Keloharju, 2004). To avoid potentially higher flat rate withholding taxes, investors might realize losses towards the end of the year.[6]

I exclude all observations of bonus certificates later than 2 p.m. on December, 30th due to the final reporting of the DAX in 2010. I report descriptive statistics for my quote data sample in Table 5.2. My sample includes 930 products issued by six dif-

[6]In Germany, the flat rate withholding tax came effective on January, 1st 2009.

TABLE 5.2: **Descriptive Statistics - Quotes.** My sample consists of 930 structured products tradable in 2010 issued by six different investment banks (A to F). This table reports the mean maturity $(T^* - t_0)/365$ (where t_0 is the issuance date) in years, moneyness $(S_{t_0} - K)/K$ (where K is the strike price and S_{t_0} the DAX level at issuance) and mean cushion to barrier H $(S_{t_0} - H)/H$ at products' issuance. Standard deviations are reported in parantheses.

Investment Bank	#Products	Maturity	Moneyness	Cushion
A	322	0.98	-0.27	0.28
		(0.62)	(0.10)	(0.17)
B	63	1.05	-0.09	0.24
		(0.43)	(0.04)	(0.11)
C	77	0.85	-0.18	0.31
		(0.34)	(0.11)	(0.15)
D	85	1.30	-0.29	0.25
		(1.15)	(0.09)	(0.27)
E	100	0.56	-0.36	0.17
		(0.28)	(0.06)	(0.08)
F	283	0.98	-0.37	0.33
		(0.53)	(0.09)	(0.21)
Total	930	0.96	-0.29	0.28
		(0.63)	(0.12)	(0.19)

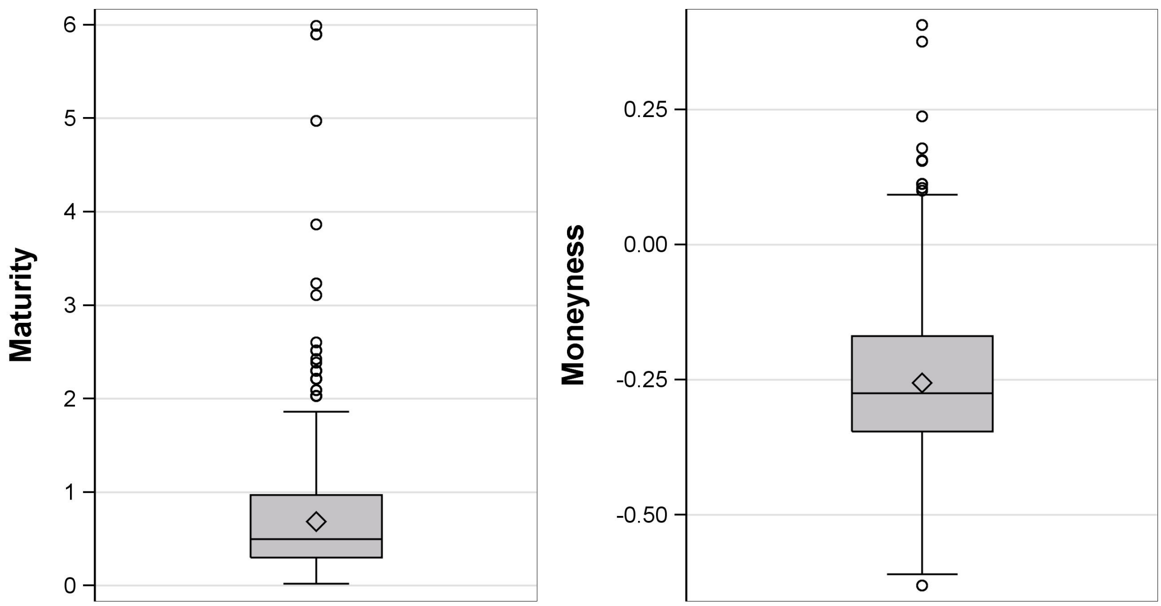

FIGURE 5.2: **Moneyness and Maturity Across Products.** This figure visualizes the average moneyness and maturity across all products and issuers for the entire sample period.

ferent investment banks, which results in 12,631,403 quotes. Products in my sample have an average time to maturity of 0.96 years and an average moneyness of -29%, which is the difference between underlying price and bonus level divided by bonus level. The average relative difference to the barrier (cushion) is 28%. However, these characteristics differ between investment banks. Due to data protection policies of the Stuttgart Stock Exchange, I make investment banks anonymous by relabeling them alphabetically. Average time to maturity ranges from 0.56 years for investment products of bank F to 1.30 years for bank D products, whereas moneyness ranges from -37% (bank F) to -9% (bank B). Figure 5.2 visualizes average maturity and moneyness across all products and observations throughout the sample period. As shown in Figure 5.3 the average moneyness across products does not vary substantially between months. However, the range of moneyness values increases towards the end of the year. Values for the cushion range from 17% (bank E) to 33% (bank F).

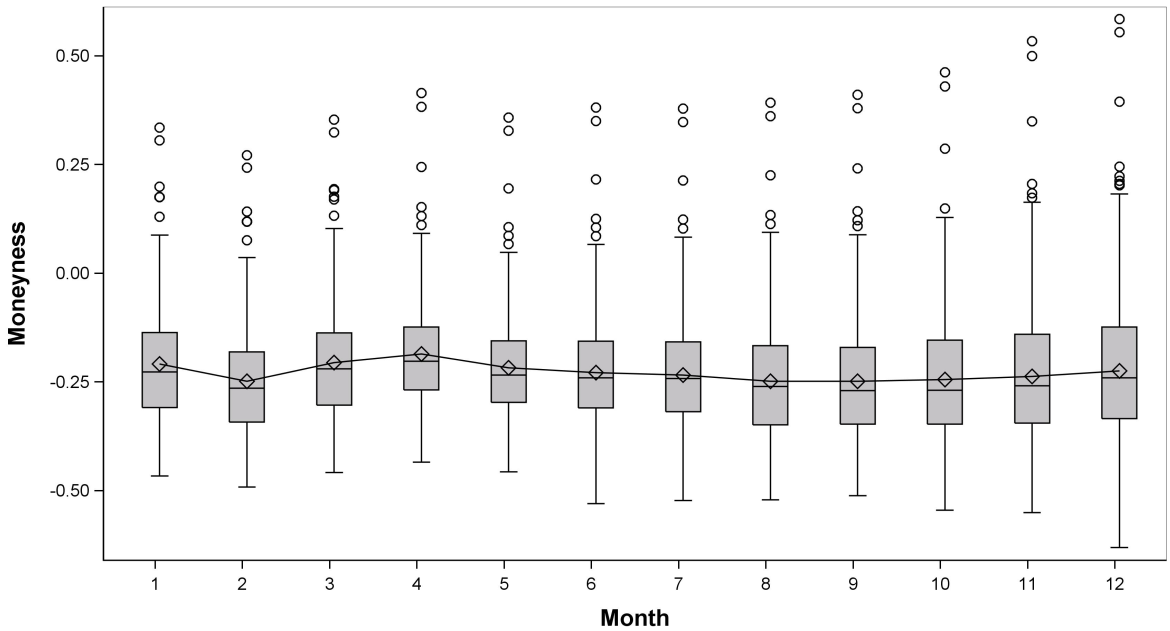

FIGURE 5.3: **Moneyness Across Products Over Time.** The x-axis shows the months of the year 2010, whereas the y-axis shows the average moneyness across products visualized as a box plot.

5.4 Results

This section presents results for all previously mentioned research questions in this chapter.

5.4.1 Premiums of Investment Banks

This section aims to provide an answer to Research Question 1a:

> **Research Question 1a.** *What is the average premium issuers include in their products?*

To measure the effect of overpricing for structured investment products, I define the absolute premium P_{it}^{abs} of a product i at time t (5 min intervals) as the difference between the observed quoted price BC_{it}^{obs} and the calculated theoretical price BC_{it}^{the}:

$$P_{it}^{\text{abs}} = BC_{it}^{\text{obs}} - BC_{it}^{\text{the}}. \tag{5.1}$$

The relative premium is defined as

$$P_{it}^{\text{rel}} = \frac{P_{it}^{\text{abs}}}{BC_{it}^{\text{obs}}} 100. \tag{5.2}$$

Refer to Section 4.2.1 for more information on the calculation of theoretical prices for bonus certificates. Since issuers do not offer free lunch and short selling is not possible in such products, I expect premiums to be positive, i.e. $P_{it}^{\text{abs}}, P_{it}^{\text{rel}} \geq 0$. Achieving arbitrage profits based on high premiums is nearly impossible for retail investors due to restricted market access, high transaction costs, and the inability to go short.

The following subsections analyze different effects and characteristics of overpricing and its impact on retail investor wealth. I report overall relative premiums in Table 5.3 clustered by issuing investment bank, since there are distinct differences between them. In total, premiums for all issuers are 2.80% across all products and days. Premiums range from -0.39% (bank B) to 4.09% (bank F). Reported results are

TABLE 5.3: **Average Issuer Premiums and Spreads - Bonus Certificates.** This table reports average spreads, and relative price deviations in percent between calculated theoretical prices and observed quotes.

Investment Bank	Premium [%]	Std. Dev.	Spread [EUR]	Spread [%]
A	2.20	3.54	0.04	0.03
B	-0.39	1.42	0.06	0.05
C	1.10	2.41	0.05	0.03
D	3.74	3.43	0.08	0.05
E	3.85	2.60	0.06	0.04
F	4.09	4.08	0.13	0.08
Total	2.80	3.74	0.07	0.05

similar to Entrop et al. (2011), although my sample has an average time to maturity of 0.97 years for which they obtain a considerably higher value of 1.74 years, which drives to some extent premiums as will be discussed later on. Premiums for bonus certificates are higher than for less complex products such as discount certificates, for which Baule (2011) finds that premiums are roughly 0.42% across all investment banks. Figure 5.4 visualizes average monthly premiums across products throughout the sample period. The monthly standard deviation of premiums - with the excep-

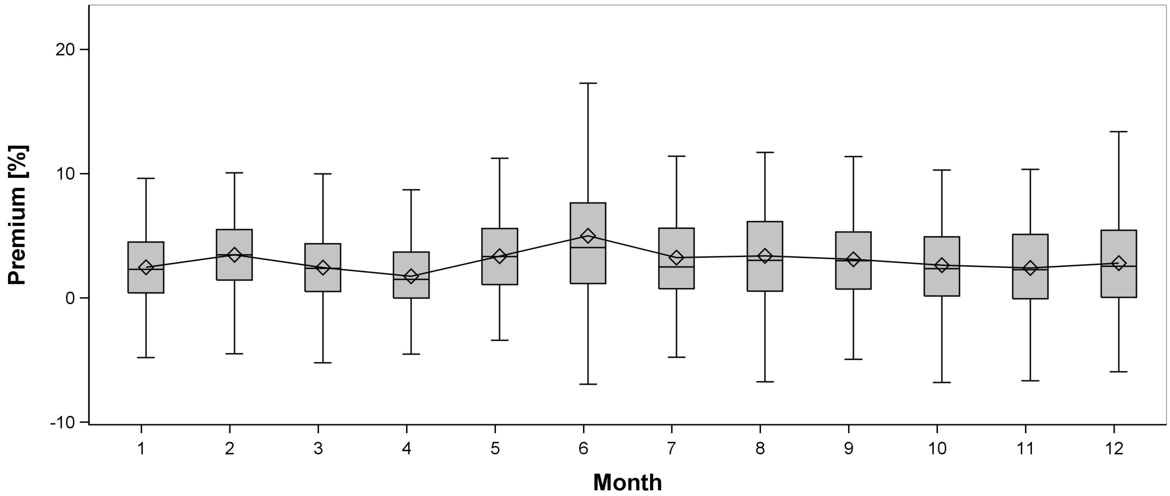

FIGURE 5.4: **Premium Across Products Over Time.** The x-axis shows the months of the year 2010, whereas the y-axis shows the average monthly premium across products visualized as a box plot.

tion of June - is roughly similar over the sample period. In June, however, standard deviations are considerably larger. Note that calculated premiums are conservative, since I do not include the default risk of the issuer in my methodological approach. Controlling for the default risk premiums should be slightly higher.

5.4.2 Intraday and Interday Effects

The pricing policy of issuers is unknown to investors. Neither do they provide sufficient information about their theoretical modeling approach, nor do they say something about their algorithms accuracy relative to their chosen model. In the following sections, I provide some empirical insights on the price-setting behavior of issuers and whether they take advantage of their strategic position and the ignorance about price modeling of retail investors. To begin with, I focus on timing influences as facilitated in Research Question 1b and 1c:

> **Research Question 1b.** *How do premiums change over the life time of structured products?*

> **Research Question 1c.** *How do premiums change during the day?*

Existing studies (see Section 3.1) are usually using daily quoted prices, i.e. EOD data, to detect issuer overpricing. I am focusing on the intraday price-setting behavior of issuers and expect product premiums to be a non-invariant function of the time of the day. I group quotes by the hour, putting the first and last 30 minutes of each trading day in a separate group, e.g. group *10:00* contains all quotes from 09:30 a.m. until 10:29 a.m. Since I use 5 min intervals this sums up to 12 quotes per product and group, ignoring the first and the last group, which each only hold 6 quotes per product. I build dummy variables *Hour* for each of the hour groups of the day. Let *RTtM* denote the relative time to maturity $(T^* - t)/(T^* - t_0)$ as proxy for the interday effect. Additionally, moneyness has been found an important factor regarding issuers' premiums (cf. Baule, 2011). Thus, let *Money* denote the moneyness $(S_t - K)/K$ for an observation for a product with strike K. To control for different pricing behaviors between investment banks, I build dummy variables *Bank* for individual investment banks. In order to explore the existence of both phenomena, intraday and interday shifts, I run a regression model across all observations of all products:

$$P_j^{\text{rel}} = \alpha + \beta\, RTtM_j + \gamma\, Money_j + \sum_{i=9, i\neq 13}^{19} \delta_i\, Hour_{ij} + \sum_{k=2}^{5} \tau_k\, Bank_{jk} + \epsilon_j, \tag{5.3}$$

where P_j^{rel} denotes the relative premium of observation j.

Prior studies show that - for some product types - issuers decrease premiums systematically during the life of an investment product, which has been called the life cycle hypothesis (Muck, 2006). Investors tend to buy structured products in the beginning of a product's life time and tend to sell it before maturity as visualized in Figure 5.5. I calculate the trading frequency across all products over the whole sample period with respect to the remaining time to maturity for each product. The buy and sell frequency appears to be diametrically opposed to each other. Hence, with a systematic decrease of premiums over time, issuers increase their rents, since, on average, investors buy for higher prices and sell for lower prices. Thus, I expect the coefficient of the remaining time to maturity to be positive, to measure the effect if issuers decrease their premiums with a reduced time to maturity. As for the intraday effect, I expect estimates of the hour dummies to be different from each other. The moneyness variable can assume positive and negative values, depending on the

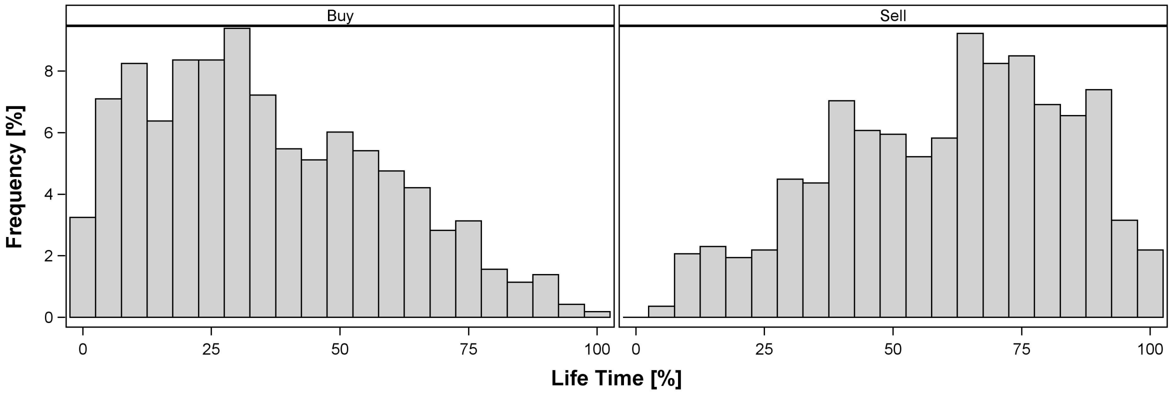

FIGURE 5.5: **Trading Frequency With Respect to Maturity.** The x-axis shows the percentage product life time that has passed, whereas the y-axis shows the trading frequency across all products in my sample.

difference between current underlying price and bonus level. Figure 5.6 visualizes the value of the incorporated barrier option of a bonus certificate with respect to the underlying price. The down-and-out put option value becomes very small for strong positive moneyness values, i.e. on the right side of the second dashed line in Figure 5.6. On the other hand, the barrier option value changes substantially for negative moneyness values. The value of the barrier option is not transparent to the investor, and thus provides the ideal environment for issuers to incorporate a higher premium as the underlying asset approaches the barrier. Nevertheless, issuers could face an increased hedging risk if the underlying approaches the barrier, since their valuation approach might result in higher model failures and, thus, inaccurate hedging positions. A higher premium would compensate the issuer for such increased risks. Therefore, I expect moneyness to have a negative effect on premiums, i.e. an increasing premium with decreasing moneyness, as also reported by Baule and Tallau (2011).

Table 5.4 reports results for the regression model differentiating between three scenarios. First, I skip the remaining time to maturity and moneyness variable to focus on the intraday effect. Second, I exclude all hour dummies but include moneyness and remaining time to maturity to measure the interday effect; and third, the combination of both. I correct standard errors for heteroscedasticity effects and serial correlation using the procedure proposed by Newey and West (1987). I find that premiums change constantly throughout the day. Premiums between 3 p.m. and 4 p.m., as well

TABLE 5.4: **Intraday and Interday Premium Shifts.** I analyze intra- and interday premium shifts for bonus certificates. *RTtM* denotes the relative time to maturity $(T^* - t)/(T^* - t_0)$, *Money* denotes the moneyness $(S_t - K)/K$ with strike K at that time. I include dummy variables for the hour of the day and individual investment banks. T-values are reported in parentheses. */**/*** denotes significance on the 5%, 1%, 0.1% level.

	Intraday	Interday	Combined
Intercept	2.17***	-3.07***	-3.09***
	(403.06)	-(498.41)	-(463.10)
RTtM		1.25***	1.25***
		(135.54)	(135.44)
Money		-21.15***	-21.15***
		(-851.20)	(-851.27)
09:00	0.03***		0.04***
	(4.84)		(7.83)
10:00	0.01*		0.01**
	(2.09)		(2.62)
11:00	0.00		0.00
	(0.76)		(1.00)
12:00	0.00		0.00
	(-0.86)		(-0.96)
14:00	0.01		0.00
	(0.27)		(1.31)
15:00	0.03***		0.02***
	(4.34)		(6.22)
16:00	0.04***		0.04***
	(7.07)		(9.90)
17:00	0.01*		0.01
	(1.97)		(1.31)
18:00	0.07***		0.07***
	(12.61)		(16.50)
19:00	0.09***		0.08***
	(12.62)		(16.88)
Bank B	-2.58***	2.37***	2.37***
	(-499.93)	(403.88)	(403.97)
Bank C	-1.10***	0.55***	0.55***
	(-135.25)	(65.83)	(65.85)
Bank D	1.54***	1.27***	1.27***
	(214.62)	(313.49)	(313.50)
Bank E	1.66***	-0.85***	-0.84***
	(207.15)	(-133.71)	(-133.50)
Bank F	1.89***	0.13***	0.13***
	(305.24)	(29.22)	(29.21)
Adj. R^2	0.12	0.57	0.57

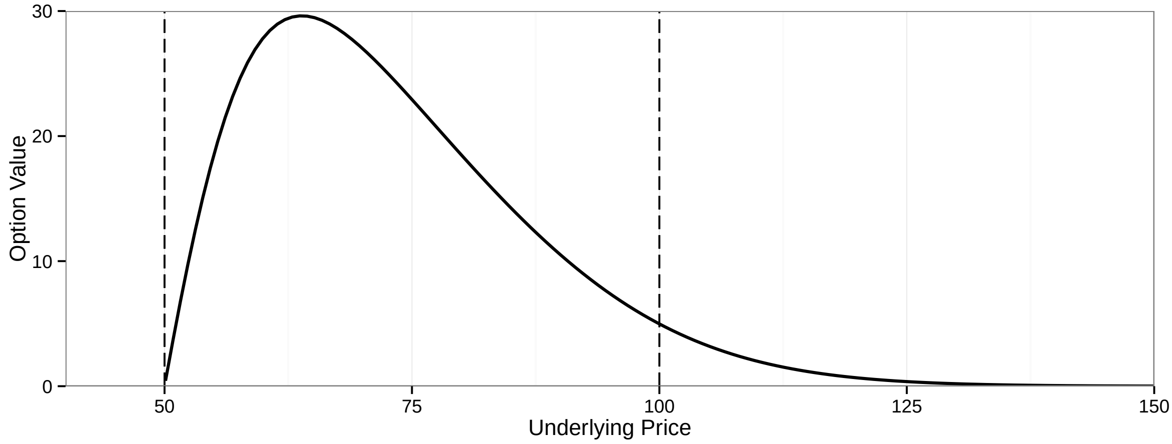

FIGURE 5.6: **Black-Scholes Value of a Down-and-out Put Option.** The x-axis shows the underlying price, whereas the y-axis shows Black-Scholes model values for a down-and-out put option with strike $K = 100$, barrier $H = 50$, volatility $\sigma = 0.15$, risk-free interest rate $r = 0.02$, time to maturity $T = 1$, and dividend yield $q = 0$.

as after 5:30 p.m., when the daily final official DAX value is reported, are higher compared to the rest of the day. For example, premiums between 6:30 p.m. and 7:00 p.m. are, on average, 0.09% higher compared to premiums at 1:00 p.m. Investment banks include an overnight (gap) risk of the underlying into their premium (cf. Entrop et al., 2011). The overnight risk should compensate issuers for potentially higher hedging costs if unexpected news hit the market and price leaps occur, which could result in an imperfect hedging situation for the issuer. Hedging costs may increase after main trading hours due to higher spreads and lower liquidity. Hence, my intraday increase in premium towards the end of the day might be due to the adjustment of prices to the overnight risk. As robustness check, I also run the regression separately for issuers. Table 5.5 reports the results. Besides for issuer C the pattern is consistent for all issuers.

Since investment banks are liquidity provider, wider spreads have to be seen as additional premium. A change in premium could therefore be offset by a reduced spread. I calculate relative and absolute spreads in basis points for all observations and find that the hour of the day and relative spreads at Stuttgart Stock Exchange are correlated with factor 0.00069, which is negligible. Absolute spread values change by just one cent within days and are typically about 7 cent, which corresponds to a 0.05% relative spread (see Table 5.3). Therefore, spreads do not matter regarding the

TABLE 5.5: **Intraday and Interday Premium Shifts - Issuer.** I analyze intra- and interday premium shifts for bonus certificates. *RTtM* denotes the relative time to maturity $(T^* - t)/(T^* - t_0)$, *Money* denotes the moneyness $(S_t - K)/K$ with strike K at time t. I include dummy variables for the hour of the day. T-values are reported in parentheses. */**/*** denotes significance on the 5%, 1%, 0.1% level.

Issuer	Intercept	RTtM	Money	09:00	10:00	11:00	12:00	14:00	15:00	16:00	17:00	18:00	19:00
A	-2.63***	0.09***	-20.35***	0.03***	0.01	0.00	-0.01	0.01	0.02***	0.03***	0.01	0.04***	0.05***
	(-848.31)	(29.24)	(-2,524.10)	(6.39)	(1.80)	(0.52)	(-1.66)	(1.56)	(5.22)	(9.28)	(1.90)	(12.37)	(12.26)
B	-0.87***	1.44***	-2.42***	0.00	0.00	0.00	0.00	0.00	0.00	0.01***	0.00	-0.02***	-0.03***
	(-340.03)	(493.74)	(-337.05)	(1.04)	(0.33)	(0.29)	(-0.19)	(1.11)	(0.37)	(4.40)	(1.29)	(-5.44)	(-7.64)
C	-1.00***	1.46***	-6.09***	0.02	0.01	0.00	-0.01	0.00	0.00	0.00	0.00	0.01	0.02
	(-91.21)	(121.89)	(-441.55)	(1.57)	(0.73)	(-0.22)	(-1.19)	(-0.04)	(0.15)	(0.33)	(0.24)	(1.25)	(1.37)
D	-1.70***	-0.33***	-20.38***	0.02**	0.01	0.01	0.01	0.00	0.01**	0.03***	0.01	0.06***	0.07***
	(-375.09)	(-71.15)	(-1,778.80)	(2.91)	(1.94)	(1.74)	(1.01)	(0.08)	(2.92)	(5.89)	(1.40)	(12.09)	(11.01)
E	-3.40***	3.20***	-14.09***	0.01	0.00	-0.07***	-0.02	-0.02	-0.01	-0.04***	-0.03*	0.02	0.04**
	(-210.43)	(242.75)	(-343.66)	(0.50)	(0.01)	(-5.78)	(-1.61)	(-1.66)	(-0.42)	(-3.29)	-(2.38)	(1.30)	(2.78)
F	-4.25***	1.28***	-23.62***	0.05***	0.01	0.01	0.00	0.00	0.03***	0.04***	-0.01	0.08***	0.10***
	(-722.24)	(232.50)	(-1,554.40)	(7.07)	(1.86)	(1.52)	(-0.50)	(0.70)	(4.96)	(6.37)	(-1.86)	(12.46)	(13.31)

timing decision of retail investors' trades. This does not apply for OTC platforms after 8 p.m., for which it can be observed that spreads are pushed further apart. Since bonus certificates are long term investment products, it usually does not matter for investors at which time of the day their orders get executed, assuming that investors do not have any knowledge about future price movements. Anticipation of intraday premium shifts could therefore increase investor profits.

As for the interday effect the regression estimate for the relative time to maturity is positive (1.25***), which means that premiums decrease with a shorter time to maturity. Put differently, investors, who bought at the issuance day and did not sell before the last day lost, on average, 1.25% through the reduction of the incorporated premium. The premium decrease throughout a product's life might not be due to the attempt to increase profits for the issuer, but by the successive amortization of issuers original distribution allowance. Although, such an allowance usually exists only for more exotic products and not for classic products such as bonus certificates.

Moneyness has a negative influence on premiums (-21.15***), which means that products closer to the barrier, i.e., where moneyness is smaller than zero, include a higher premium than those with a higher moneyness. Dummy variables for banks indicate that premiums for banks D, E and F are, on average, higher than premiums of bank A, whereas premiums of bank B and C are lower on average, which can be also seen in Table 5.3.

If the barrier has been touched the bonus payment is gone and the theoretical price of such a product is in my case simply the value of the underlying index multiplied with the subscription ratio because there are no dividend payments. Since the complexity of the product decreased substantially and risks are highly reduced for the issuer one might expect the premium to be non-time-dependent anymore. In fact by running the simple regression model

$$P_j^{\text{rel}} = \alpha + \beta RTtM_j + \epsilon_j \tag{5.4}$$

for all observations for bonus certificates that are bonus-free I still observe a strong significant effect of the relative remaining time to maturity ($\alpha = 0.28^{***}, \beta = 0.43^{***}$). Such premiums cannot be mistaken for risk compensation of issuers, but for the purpose to increase profits. This fact also confirms that a part of the premium is added at issuing date and decreases continuously until maturity regardless of the actual development of any underlying factors.

5.4.3 Risk and Demand Effects

As shown in the former section, there are intraday as well as interday influences on premiums. Some effects can be explained through the life cycle hypothesis or the overnight risk. In order to evaluate, independently from timing factors, whether market risk and investor demand have any effect on the pricing policy of investment banks, as facilitated in the following research question, I run another regression.

Research Question 1d. *Are issuers anticipating retail investor demand?*

To capture market risk, I calculate a volatility measure adapted to my purpose. Let $Vola_j$ denote the relative range of the underlying within the last five minutes before observation j. Let p_t denote the underlying price at time t (in minutes), and let $t_0(j)$ be the time of observation j. $Vola_j$ is then calculated as follows:

$$\begin{aligned} Vola_j = &\left(\max_{t_0(j)-5 \le t \le t_0(j)} p_t - \min_{t_0(j)-5 \le t \le t_0(j)} p_t \right) \\ &\left(\frac{1}{2} \left(\max_{t_0(j)-5 \le t \le t_0(j)} p_t + \min_{t_0(j)-5 \le t \le t_0(j)} p_t \right) \right)^{-1} 100. \end{aligned} \tag{5.5}$$

My regression model is then defined as follows:

$$P_j^{\text{rel}} = \alpha + \beta Sell_j + \gamma\, Buy_j + \delta\, Vola_j + \sum_{k=2}^{5} \tau_k\, Bank_{jk} + \epsilon_j, \tag{5.6}$$

where the *Buy* and *Sell* variable are dummies that are set to one if between the last observation and the current observation a buy or sell order was executed, respectively. All other variables are as defined before. Table 5.6 reports results for three different variations of the regression model. First, I skip the volatility variable (*Demand*); second, I exclude the buy and sell dummies (*Risk*), and, third, I run the model including all variables (*Combined*). I observe a positive estimate for the buy dummy and a negative estimate for the sell dummy. Generally, this could be interpreted as a way of influencing the attractiveness of a product, similar to a classic dealer response

TABLE 5.6: **Risk and Demand Effects.** This table reports effects of risk and demand on issuers' premiums. I run the following regression $P_j^{\text{rel}} = \alpha + \beta Sell_j + \gamma\, Buy_j + \delta\, Vola_j + \sum_{k=2}^{5} \tau_k\, Bank_{j,k} + \epsilon$, where the *buy* and *sell* variable are dummies that are set to one if between the last observation and the current observation a buy or sell order was executed. *Vola* measures the relative range of the underlying within the last five minutes before each observation. All other variables are as defined before. T-values are reported in parentheses. */**/*** denotes significance on the 5%, 1%, 0.1% level.

	Demand	Risk	Combined
Intercept	2.20***	1.92***	1.92***
	(1,355.46)	(862.16)	(862.10)
Buy	1.43***		1.37***
	(21.17)		(19.94)
Sell	-0.69***		-0.72***
	(-7.18)		(-7.44)
Vola		2.44***	2.44***
		(194.29)	(194.22)
Bank B	-2.58***	-2.59***	-2.59***
	(-653.82)	(-614.96)	(-614.95)
Bank C	-1.10***	-1.04***	-1.04***
	(-217.93)	(-194.16)	(-194.21)
Bank D	1.54***	1.53***	1.53***
	(497.94)	(463.01)	(463.06)
Bank E	1.66***	1.72***	1.72***
	(325.36)	(315.82)	(315.78)
Bank F	1.89***	1.89***	1.89***
	(767.19)	(718.05)	(718.02)
Adj. R^2	0.12	0.13	0.13

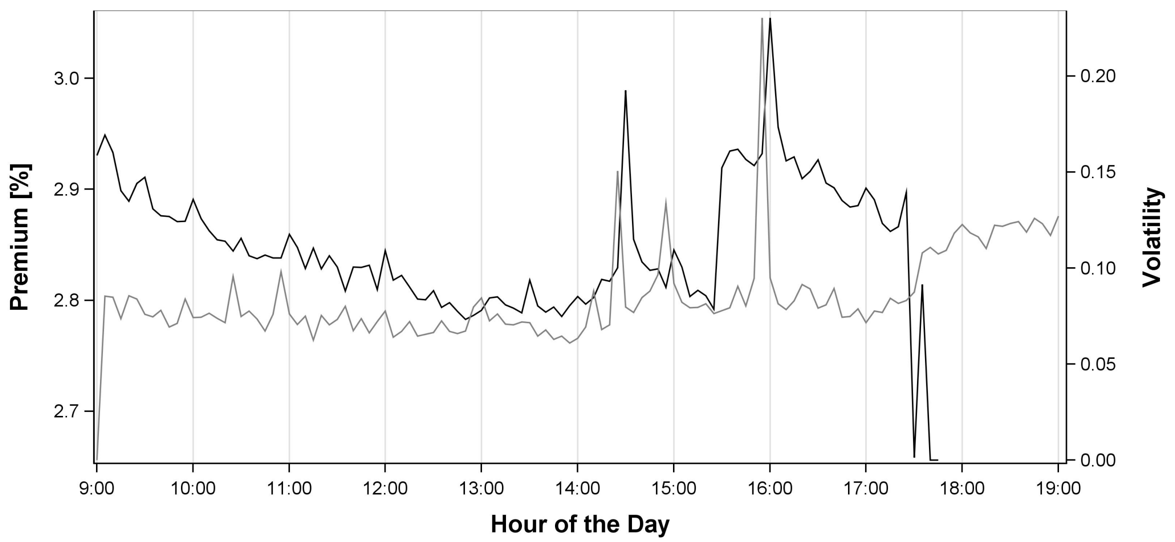

FIGURE 5.7: **Average Intraday Premium and Volatility.** The x-axis shows the hour of the day, whereas the y-axis shows volatility and percentage premium. The black lines denotes volatility, whereas the gray line represents relative premium.

in a hybrid market (cf. Harris, 2003). If a sell order of an investor is executed, less shares of the product are outstanding and this way investment banks do make less risk-free profits. By decreasing the premium after a sell order, the price of the product is better compared to competing products and more order flow may be attracted by it. Another explanation is that issuers are decreasing premiums when they expect sell orders to dominate and increase them if they expect buy orders to dominate. As a result issuers would increase their profits. Those results support Baule (2011), who uses order flow imbalances to analyze this phenomena.

The estimate for the volatility parameter is positive (2.44***), which makes it easy to conclude that a higher volatility, and therefore higher potential risks and associated hedging costs for the issuing bank, increase premiums substantially. Figure 5.7 visualizes average premiums across products, and the average underlying volatility throughout the day based on five minute intervals. I observe that the highest premium peaks are consistent with a strong increase in volatility. The peak is roughly at 3:30 p.m., at the time when markets in the USA are opening. It seems that high uncertainty of price movements is reflected in premiums of structured investment products.

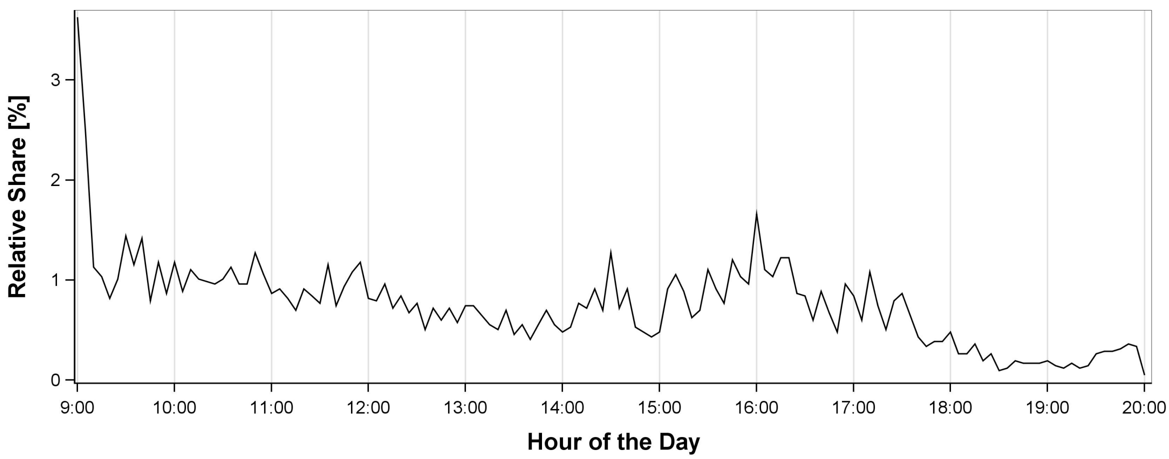

FIGURE 5.8: **Relative Intraday Trade Frequency.** This figure visualizes the average relative frequency of all trades included in my sample. The x-axis shows the hour of the day, whereas the y-axis shows the percentage of executed trades within the individual hour.

5.4.4 Premium Impact on Retail Investor Wealth

Investor wealth is reduced through premiums of investment banks. Nevertheless, premiums are necessary to compensate banks for arising risks, hedging costs, and the service they provide to fulfill strategies for retail investors that would not be possible otherwise. Investment banks shift premiums during the day and over the life time of their investment products as shown in Section 5.4.2. I study the influence of those intraday and interday shifts in premium on retail investors wealth, as stated in the following research question.

> **Research Question 1e.** *What is the impact of premium changes on wealth of investors?*

To answer this question, I conduct a simple method based on retail trading data from Stuttgart Stock Exchange. Obviously, retail investors' trade frequency is not homogeneous throughout the day. Figure 5.8 visualizes their intraday trading activity based on all trades in my sample. Ignoring the peak of executed orders at 9:00 a.m., which contains all orders that have been sent to the exchange outside trading hours, the highest relative share of executed orders is at 4:00 p.m.. This is very likely due to the market opening in the U.S., which usually induces increased market activity in Germany. Since I already know that premiums are high at that time and after the final

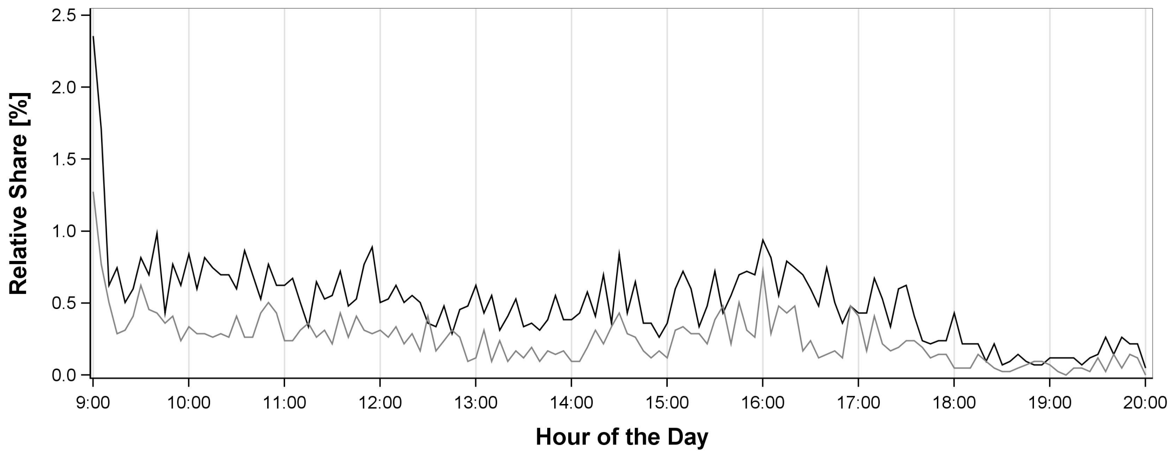

FIGURE 5.9: **Relative Intraday Buy and Sell Frequency.** This figure visualizes the average relative frequency of all executed buy and sell orders included in my sample. The x-axis shows the hour of the day, whereas the y-axis shows the percentage of executed buy and sell orders relative to all trades. The black line denotes buy orders, whereas the gray line represents sell orders.

daily closing price for the DAX (cf. Figure 5.7), I expect intraday premium shifts to have an influence on investors' wealth.

Figure 5.9 shows the intraday trade frequency separated by trade direction across all products and throughout the whole sample period. Interestingly, referring to the time of order execution, I do not observe a different behavior of retail investors regarding their decision to buy or sell bonus certificates. Graphs for the relative number of buy and sell orders move very alike. In total there are more executed buy orders than sell orders, which is probably due to the fact that investors can hold their products until maturity. The value of the product is cashed out automatically by the individual broker at that date without the need to sell it.

In the following I analyze how changes in premium are reflected in the wealth of retail investors. Hence, I measure the intraday and interday impact for all trades in product i by calculating an imbalance based on order size and the absolute premium of the corresponding issuer for the product at that time. Let B_i and S_i denote the set of all executed buy and sell orders in product i, respectively. Moreover, let $|B_i|$ and $|S_i|$ denote the number of buy and sell orders in product i, respectively. I define the premium impact PI_i as

$$\mathrm{PI}_i = \frac{\sum\limits_{j \in B_i} -s_j P^{abs}_{it_0(j)} + \sum\limits_{k \in S_i} s_k P^{abs}_{it_0(k)}}{\sum\limits_{j \in B_i} s_j p_j} 100, \tag{5.7}$$

where s_l denotes the size of trade l, p_l denotes the execution price of trade l, and $t_0(l)$ denotes the timestamp of the particular trade. I round trade timestamps up to 5 min intervals to match my quote data. My premium impact measure is only comparable across products if, for an individual product, the same number of shares have been bought and sold during my sample period. Hence, if the aggregated number of shares traded in product i is not equal to zero at the end of the observation period, i.e.

$$\sum_{j \in B_i} s_j - \sum_{k \in S_i} s_k \neq 0, \tag{5.8}$$

I assume the buy or sell, depending on a positive or negative inventory, of the residual shares given the last observed premium. For example, if until the end of my sample period investors sold 100 shares less than they bought of product i, I assume the sell of 100 shares with respect to last observed premium for product i. This way, I always receive an outstanding number of zero shares and thus make the premium impact comparable across products. If the measure above is significantly different from zero, investors are affected by intraday and interday premium changes. Note that investors would benefit from changes in premium if $\mathrm{PI} > 0$ on average.

To further study the premium effect, I break down the premium impact measure into intraday and interday effects. However, it has to be mentioned that this is not possible in a exact way, thus the addition of outcomes of the intraday and interday measures is not the same as the overall premium impact measure. Nevertheless, the intraday and interday measure try to capture the effects as good as possible.

Assume the same setting as above. Let $\overline{P}^{abs}_{iD(l)}$ denote the mean absolute premium of product i at the day when trade l was executed. I model the intraday premium impact as follows:

$$\text{PI}_{iD}^{\text{Intra}} = \frac{\sum\limits_{j\in B_i} -s_j\left(P_{it_0(j)}^{abs} - \overline{P}_{iD(j)}^{abs}\right) + \sum\limits_{k\in S_i} s_k\left(P_{it_0(k)}^{abs} - \overline{P}_{iD(k)}^{abs}\right)}{\sum\limits_{j\in B_i} s_j p_j} 100. \tag{5.9}$$

Basically, I sum up the differences between premiums at individual trade timestamps and the corresponding daily mean of premiums with respect to the invested volume. To measure explicitly the interday effect, I ignore premium fluctuations during the day and, thus, use the original premium impact measure with daily average premiums instead of premiums at the exact trade timestamp:

$$\text{PI}_{i}^{\text{Inter}} = \frac{\sum\limits_{j\in B_i} -s_j\overline{P}_{iD(j)}^{abs} + \sum\limits_{j\in S_i} s_j\overline{P}_{iD(k)}^{abs}}{\sum\limits_{j\in B_i} s_j p_j} 100. \tag{5.10}$$

I expect the interday effect to be far greater than the intraday effect, since it is the ideal way to anticipate retail investor trading behavior. The reduction of the premium over time and, thus, the slightly reduction of potential returns has to be accepted by investors, provided that they choose bonus certificates as their desired investment opportunity. To gain profits following their long term investment strategy they have to tolerate that investment banks will take their share of those profits. However, this passive way of reducing investors profits is hard to detect for the common investor. Results for all three measures are reported in Table 5.7.

For the first measure, the combination of both premium effects, I observe estimates from -1.37% (bank F) to -0.40% (bank D), at which all estimates but for bank D are significant. On average, retail investors lose roughly 1% of their invested capital due to shifts in premium. It seems likely that investment banks are using shifts in premium to obtain additional benefits at the expense of retail investors.

By breaking up those effects into intraday and interday shifts, I observe that intraday losses range from 0.23% for bank A to 0.00% for bank E. Interday effects are substantially larger than intraday effects as expected. Losses range from 1.19% (bank F) to 0.20% (bank D). Summarizing, bad timing reduces investor wealth by 0.17% on average, but holding products over long periods substantially reduces wealth by

TABLE 5.7: **Impact on Retail Investors Wealth.** This table reports retail investors losses due to intraday and interday premium changes. Results are reported in total and for each investment bank separately. T-values are reported in parentheses. */**/*** denotes significance on the 5%, 1%, 0.1% level.

	All	A	B	C	D	E	F
Combined							
Average Premium Shift Losses [%]	-0.97***	-1.03***	-0.42***	-0.72***	-0.40	-0.56***	-1.37***
T-Value	(-5.02)	(-3.76)	(-2.82)	(-4.44)	(-0.58)	(-4.87)	(-2.89)
Intraday							
Average Premium Shift Losses [%]	-0.17*	-0.23	-0.04	-0.01	-0.20	0.00	-0.19
T-Value	(-1.92)	(-1.08)	(-1.18)	(-0.56)	(-1.48)	(-0.08)	(-1.74)
Interday							
Average Premium Shift Losses [%]	-0.80***	-0.81***	-0.38**	-0.74**	-0.20	-0.56****	-1.19**
T-Stat	(-4.23)	(-4.76)	(-2.49)	(-4.72)	(-0.25)	(-4.87)	(-2.29)

0.80%.

In the following I extend the prior analysis by focusing briefly on the effect of complexity on the pricing behavior of issuers. Besides already mentioned influencing factors, the complexity of the environment or the product might have an influence on issuers' premiums.

5.4.5 Complexity Effect

The success of these products and competition between the issuing banks appears to be leading issuers to introduce more and more complex products. The payoff profiles are becoming so complex that, at least, the average investor is unable to price them. The increase in the number of possible products is making the comparison of similar products across issuers onerous. Nonetheless, investors appetite for these products appears to be unsated, perhaps to the detriment of their investment goals. This section aims to provide a brief overview of the complexity effect on the premiums and competition of issuers as facilitated in the following research question.

> **Research Question 1f.** *What is the effect of complexity on premiums and competition of issuers?*

Related Work. The study of the impact of complexity on investors' welfare and decision making is relatively new. Brunnermeier and Oehmke (2009) provide an overview of complexity in financial markets and address a number of questions about the regulation, definition, and ways to deal with complexity. Carlin (2009) develops a model that studies complexity in retail financial markets under competition. Ellison and Wolitzky (2012) develop a model in which firms engage in obfuscation when selling a homogeneous good to consumers who incur search costs. They show that as long as obfuscation, which is positively correlated with search costs, is costless, obfuscation must occur in equilibrium. Carlin and Manso (2010) show that educational programs designed to increase investor sophistication may actually increase the complexity in a market.

Little empirical evidence exists on the direct impact of complexity on investor welfare, investor behavior, or portfolio decisions. One exception is the experimental study presented in Carlin et al. (2013). They show that increased complexity leads to lower liquidity, higher volatility, and less price efficiency. The experiment generally confirms the conjecture that investors do not deal well with complex decisions. Arora et al. (2011) show, even in markets with fully rational investors, that asymmetrically distributed computational resources required to price certain derivatives can cause market imperfections associated with asymmetric information.

Methodology and Results. Adding complexity to the structure of a product makes the calculation of the true price more costly, i.e. the more components a product has the harder it is for investors to derive fair prices. In the following, I study briefly two additional product types, discount certificates and capped bonus certificates, to measure the influence of additional components in the product structure on issuer premiums. Both product types are related to classic bonus certificates. Discount certificates are easier to understand and less complex due to missing barrier options, whereas capped bonus certificates add a component to bonus certificates through the additional capped payoff. Refer to Section 4.2.1 for more information on the individual product structure. I calculate theoretical prices for both product types analogous to the former sections. However, I base calculations on EOD data for the year 2010 for all products having a DAX constituent or the DAX itself as underlying. Therefore, I retrieve additional EUREX option data on a daily basis for all DAX constituents from SIRCA. In total, I analyze 9,550 discount certificates and 4,684 capped bonus certificates issued by the same investment banks as before. Table 5.8 reports premiums for both product types across all products and distinguished by issuer.

Premiums for discount certificates are very low on average, ranging between 0.10% (bank D) and 0.53% (bank A), compared to bonus certificates. Discount certificates are the most popular product type in Germany. Due to the more comprehensible structure and the huge competition across issuers premiums might be pushed to the lowest extent possible. However, premiums for capped bonus certificates are substantially higher, ranging between 3.71% (bank A) and 4.57% (bank F) across all products, which can be seen in favor of the assumption that higher complexity leads to obfuscation and therefore allows for higher premiums. Nevertheless, from an outside perspective it is not possible to assess to which extent a more complex product structure increases costs on the issuer side.

TABLE 5.8: **Average Issuer Premiums - Discount and Capped Bonus Certificates.** This table reports average relative price deviations in percent between calculated theoretical prices and observed quotes for discount certificates and capped bonus certificates.

	Discount Certificates			Capped Bonus Certificates		
Investment Bank	#	Premium [%]	Std. Dev	#	Premium [%]	Std. Dev
A	1,730	0.53	1.56	1,172	3.71	4.57
B	3,662	0.38	1.75	946	3.95	4.69
C	3,168	0.52	1.55	1,296	4.34	5.22
D	830	0.10	1.34	129	4.28	4.29
E	0	n/a	n/a	265	4.43	5.84
F	160	0.46	1.03	876	4.57	5.12
Total	9,550	0.43	1.61	4,684	4.13	4.92

Similarly, by increasing the number of similar but not exactly comparable products issuers increase the search costs for investors such that they are unable to learn the true (market) price from the prices of other products. In the following I study products tradable at Stuttgart Stock Exchange between January 1, 2009 and December 31, 2011. More precisely, I focus on discount certificates, bonus certificates, and capped bonus certificates. For each product I analyze whether products with the exact same or slightly similar characteristics are available. In the following, I call those products substitutes. Figure 5.10 visualizes the workflow of the algorithm to find substitutes. The algorithm passes step-by-step through all products and searches for each individual product all available substitutes based on the specific configuration. If it finds at least one substitute the result is 1 else 0.

I use four different configurations to find substitutes. All of them assume that available substitutes should be of the same overall option type (call or put) and designated on the same underlying asset. Other characteristics, the algorithm is based on to find substitutes, are: first trading day, last trading day, barrier level, bonus level, and cap level. Those are varied between configurations (model A to D). Model A defines a substitute as a product that is identical to the chosen product with respect to all mentioned characteristics but the issuer. Model B is more flexible, allowing the bonus level, barrier level, and cap level to deviate by 5% of the value of the reference product to still ensure it being labeled as a substitute. For example, assume a discount certificate *DC* with a cap of EUR 10. All discount certificates on the same underly-

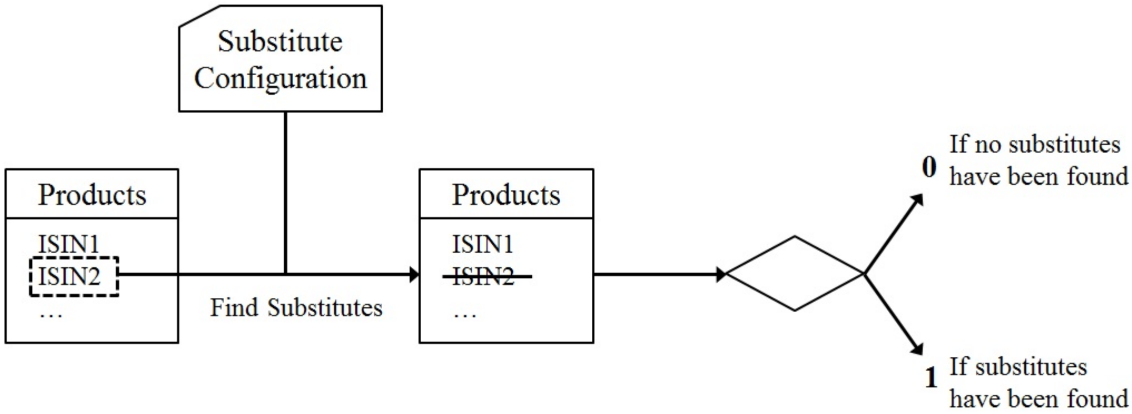

FIGURE 5.10: **Substitute Algorithm Workflow.** This figure visualizes the workflow to find similar products across the master data set of Stuttgart Stock Exchange.

ing, with the same option type (always true in case of discount certificates), the same first and last trading day, and a cap between EUR 9.50 and EUR 10.50 are defined substitutes to *DC*. Model C and D are similar variations such as the first two models but with the additional variation of the first and last trading day. Table 5.9 shows the percentage number of products that have at least one substitute, distinguished by models A to D.

In total my data sets amounts to 443,672 discount certificates, 119,465 bonus certificates, and 194,686 capped bonus certificates. However, only 0.95% of all discount certificates have at least one substitute, which allows for a perfect comparison of quoted prices. For classic and capped bonus certificates I observe a perfect substitute ratio of 0.31% and 0.82%, respectively. Allowing a deviation up to 5% for bonus, cap, and barrier level I observe that 40.88% of all discount certificates, 49.99% of all bonus certificates, and 53.25% of all capped bonus certificates have at least one substitute. Keeping bonus, cap, and barrier level fixed, but allowing for a 5% deviation of the first and last trading, relative to the total life time in days, results in a considerably lower number of products that have substitutes.

Concluding, given the large number of products for all three product types, products are issued on a dense grid regarding their characteristics but most of them are not quite comparable to other tradable products. Due to the complex pricing of the incorporated barrier options in case of bonus certificates, a simple comparison is not possible between products with even only slightly different characteristics. Thus, investors face higher search costs regarding their investment decision and do not end up necessarily with the best priced product.

5.5 Conclusion

Investment banks design financial products for retail investors offering risk-return profiles that cannot be achieved with regular stocks or bonds. For structured products traded in Germany investment banks act solely as liquidity provider and therefore prices are set by them and only influenced by direct price competition[7]. This market structure makes it possible for investment banks to include a premium in their prices to obtain risk-free profits and compensate themselves for possible risks.

In this chapter I evaluate intraday and interday shifts in such premiums for German structured investment products. I calculate theoretical prices for each product and find observed prices to be higher than calculated theoretical prices. I provide evidence that issuers' premiums, i.e. the difference between theoretical and observed prices, are changing throughout the day and increase towards the end of the day. Premiums are high during the time of the US market opening and towards the end of the day, after the final official daily reporting of the underlying. Regarding the interday effect, I find that investment banks reduce premiums of products over the life time to achieve additional benefits on the expense of their customers.

I evaluate two possible explanations for the premium adjustments: risk and investor demand. I find that volatility has a positive influence on premiums. Looking at hourly averages for premiums I find that the intraday peak of premiums falls within the average peak of volatility around the time when markets in the US are opening. I observe a positive effect on premiums when shares are bought, and a negative impact when shares are sold, which represents the fact that investment banks are anticipating investor order flow. One explanation is that investment banks increase premiums when they expect buy orders to dominate, and decrease premiums when sell orders seem to dominate as shown by Baule (2011). This way they increase their own profits on the expense of retail investors.

[7] Nevertheless it is possible that there are customer orders at Stuttgart Stock Exchange against which an order could be executed. This happens in less than 0.01% of all trades.

TABLE 5.9: **Substitutes.** This table captures the percentage share of products that have at least one substitute, i.e. a product that has the same or slightly similar characteristics. Four different configurations (model A to D) are used to find substitutes, based on the following characteristics: underlying, option type, first trading day, last trading day, bonus level, barrier level, and cap. ●denotes that the specific attribute has to be identical, ◐represents an extended leeway for the attribute, allowing for deviations of up to 5% with respect to the reference value of the product. Values in the last row (Total) represent the total number of products studied.

					Discount Certificate		Bonus Certificate			Capped Bonus Certificate			
Model	Identical Underlying	Identical Option Type	Identical First-Trading-Day	Identical Last-Trading-Day	Identical Cap	Substitutes [%]	Identical Bonus Level	Identical Barrier	Substitutes [%]	Identical Bonus Level	Identical Barrier	Identical Cap	Substitutes [%]
A	●	●	●	●	●	0.95	●	●	0.31	●	●	●	0.82
B	●	●	●	●	◐	40.85	◐	◐	49.99	◐	◐	◐	53.25
C	●	●	◐	◐	●	35.05	●	●	5.68	●	●	●	6.16
D	●	●	◐	◐	◐	66.36	◐	◐	87.72	◐	◐	◐	90.45
Total						443,672			119,465				194,686

Since short selling is not possible for those products, retail investors are always negatively affected by those reductions. I examine those intra- and interday effects on retail investors wealth using a trade data set from Stuttgart Stock Exchange. I find that investors lose on average roughly 1% by shifts in premium. I find that interday shifts in premium have a far greater effect on investor wealth than timing effects during the day. On average investors lose 0.17% through bad timing of their orders, whereas holding the product leaves investors with an average loss of 0.80%. Unfortunately, the loss occurring through holding the product over its life time cannot be avoided if investors are convinced of buying such products.

Additionally, I analyze premiums of less and more complex products compared to bonus certificates. Premiums for discount certificates are substantially lower on average, whereas premiums for capped bonus certificates are higher relative to bonus certificates. Referring to the decision complexity of retail investors, I examine the availability of similar products. If products would exist with the same characteristics direct price comparisons would be possible and thus may increase price competition and lead to lower premiums as a result. However, only for 0.95% (0.31%) of all discount certificates (bonus certificates) an identical product of another issuer can be found. This leads to the assumption that, although, products are issued in a very dense grid on several underlyings, issuers try to avoid situations where easy price comparisons are possible.

Concluding, my study quantifies the premium investment banks charge for their service of providing complex investment products and hereby supports related research. In addition, I analyze premium behavior during trading days and find systematic premium adjustments. Whether the premiums are actually too high to be justified must be considered by the investor or by regulatory instances. I point out, however, that my premium calculations are conservative in the sense that I do not account for possible scale effects as well as for the inherent default risk of the issuer. Either way, improvements in transparency of structured products like bonus certificates could increase retail investors' wealth. Analogously, they would profit from a higher price competition between investment bank participating in the certificate market.

Chapter 6

Retail Investors' Trading Behavior

"Las Vegas is busy every day, so we know that not everyone is rational."

Charles D. Ellis (Former Managing Partner of Greenwich Associates)

6.1 Introduction

TRADITIONALLY, retail investors' activity in financial markets was motivated by building up one part of their overall retirement savings plan. Retail investors only rarely engaged in short-term speculation, but rather followed conservative long-term investment strategies. Most securities had comprehensible risk-return combinations and retail investors did not have access to sophisticated trading strategies and opportunities to speculate on falling prices. This changed dramatically with the introduction of structured products, specifically designed to grant retail investors access to sophisticated trading strategies and risk-return profiles for a broad range of different market expectations. This financial market innovation has reduced the gap between institutional and retail investors significantly. However, it remains unanswered if this innovation is beneficial for the wealth of retail investors.

Today's attitude of retail investors towards financial markets is no longer just a question of investing, but also includes speculation, and gambling as motivational factors. Many investors may think they have valuable information and can successfully speculate on future market movements, but more often it may just be an excuse to purse the gambling excitement and the thrill of adrenaline. Several studies have shown that retail investors lose on average due to excessive trading (Odean, 1999; Barber et al., 2009; Barber and Odean, 2000).[1] Barber and Odean (2000) state it pragmatically: "Active investment strategies will under perform passive investment strategies."[2]

In Germany, the market for structured products provides an ideal environment for retail investors to trade excessively, speculate and gamble on ongoing trends and market movements. Retail investors have easy access to leveraged bank-issued derivatives on stocks or indices which greatly magnify price fluctuations of the respective underlying. So far, there are no empirical investigations whether investors use leverage products to incorporate private information and gain leveraged benefits, or whether it is primarily used as a casino-like 'financial playground' that facilitates retail investor gambling. In this chapter, I address this question by analyzing how (un)skillful retail investor trading in leverage products is.

A growing body of literature provides evidence that gambling is an important driver of retail investor trading activity: investors motivated by entertainment (Dorn and Sengmueller, 2009) or sensation seeking (Grinblatt and Keloharju, 2009) trade way more frequently than others.[3] Further, retail investors are attracted to assets with characteristics of a lottery, such as a high skewness of returns (Han and Kumar, 2012; Brunnermeier and Parker, 2007; Garrett and Sobel, 1999; Gao and Lin, 2012). Put differently, retail investors pay little attention to the expected return of an asset and give too much weight on the potential to generate extreme positive returns. Kumar (2009) finds that trades in lottery-like assets have a negative impact on investors' portfolio performance and Kumar et al. (2012) even observe a herding effect of such trades. As for the derivatives market Doran et al. (2011) find that retail investors are more attracted by lottery-like assets, such as out-of-the-money options, around New

[1]See Section 3.2 for a more detailed literature overview.
[2]p. 800, Barber and Odean (2000).
[3]Dorn and Sengmueller (2009) show that retail investors trading for entertainment trade 'twice as much as those who fail to take pleasure in gambling or investing[...]', p. 602.

Year. Retail investor sentiment measures, trading volume and Las Vegas gambling volume supports their hypothesis. Lakonishok et al. (2007) find that a huge number of non-market maker option trades can be attributed to speculation on the underlying asset prices, whereas Bauer et al. (2009) find evidence for gambling in the option market and conclude that retail investors lose due to excessive trading and bad market timing. Hedging as an important explanation for retail investors to trade leveraged derivatives is rejected by Bauer et al. (2009) and Schmitz and Weber (2012). Anderson (2008) empirically finds that investors who are likely to gamble are those with less capital at hand. Dorn et al. (2012) document a substitution effect between state lotteries and retail trading, and find that this effect is more pronounced for less educated male retail traders. Bauer et al. (2009) add to this with the result that "single men with low income and little investment experience are most likely to engage in [...] option trading [...]."[4]

In sum, retail investors who gamble in financial markets can be assigned three characteristics: (i) they trade frequently, (ii) they perform poorly, and (iii) they favor higher risk and leverage. I contribute to the literature by answering the following questions: do retail investors speculate successfully on short time horizons? How informed are retail investors? I analyze whether retail investor trading is informed in three dimensions: (i) profitability, (ii) news trading, and (iii) transaction costs. I analyze profitability of trades with respect to volume, leverage and order type.

As already pointed out in Section 2.3 leverage products consist of two distinct product types: Warrants and knock-out warrants. In my analysis I focus on knock-out warrants instead of (classic) warrants, since knock-out warrants are hardly suitable for hedging purposes. I distinguish all results by the type of underlying (index vs. individual stocks). I find that raw returns are negative for products with stocks as underlying, and only partially positive for those with index as underlying. However, sharpe ratios are smaller than 0.3 on average, which indicates a poor risk-adjusted performance. I analyze performance with respect to implicit and explicit transaction costs and find that investor's losses are largely influenced by them, reducing returns roughly by 6% on average.

I find that trading activity of retail investors increases substantially around news.

[4]Quotation extracted from p. 745.

However, the performance of trading around news announcements is equally poor as the trading performance at any other point in time.

The remainder of this chapter is structured as follows: Section 6.2 defines research questions addressed in this chapter. My sample is described in Section 6.3, including descriptive statistics. Section 6.4 shows empirical results. More precisely, Section 6.4.1 reports result for the overall performance, Section 6.4.2 analyzes influencing factors such as volume, leverage ratio, and order type, and Section 6.4.3 analyzes whether news trading is informed. Finally, Section 6.5 concludes.

6.2 Research Questions

This chapter deals with the behavior of retail investors with respect to short term speculation. The overall research question for this chapter is as follows:

> **Research Question 2.** *Is trading in structured products beneficial for retail investors wealth?*

Similar to the preceding chapter I specify more detailed research questions grouped under the above umbrella question. The straight forward approach to measure successful retail investor trading is analyzing the actual performance on a trade-by-trade basis, which is addressed in in the following research question.

> **Research Question 2a.** *Are retail investors trading successfully in leverage products?*

However, several studies have shown that retail investor performance is mostly driven by the underestimation of transaction costs. Therefore, I break down performance without explicit and implicit transaction costs. Although, this is not a realistic scenario, it still reveals if investors are not entirely sensitive to the costs of trading.

> **Research Question 2b.** *Which effect do transaction costs have on the performance of retail investors?*

The price of an asset reflects the information available to market participants. I test which effect the arrival of new information has on the behavior of retail investors as stated in the following research question:

Research Question 2c. *How do retail investors react to new information?*

More precisely, I am interested in whether retail investors react to new information before or/and after it has been published. Additionally, I will shed light on the actual performance of investors trading around the arrival of new information. The following section describes the studied sample in more detail and presents descriptive statistics.

6.3 Sample Selection and Descriptive Statistics

I focus on knock-out warrants, designed for short-term speculation or gambling. My sample period covers 238 trading days, ranging from April 1, 2009 until February 28, 2010. I obtain retail investor trade data and master data from Stuttgart Stock Exchange for all tradable knock-out warrants. Stuttgart Stock Exchange is Germany's leading stock exchange for retail investors and Europe's leading specialist stock exchange for structured products. It exclusively attracts order flow from retail investors and thus provides a unique environment to study the behavior of this group of investors. Algorithmic and high-frequency traders are banned from this exchange.

I build product quintiles according to the aggregated total trading volume for each knock-out warrants. As sample, I focus on the 20% most traded of all knock-out warrants with the German stock market index DAX as underlying. They account for approximately 70% of the total trading volume. Additionally, I include all traded knock-out warrants with a stock as underlying that has been a DAX constituent during the sample period.[5] I retrieve quote data on a one minute basis for each product throughout the sample period from TRDTH through SIRCA. I exclude knock-out warrants for which no quote data can be obtained through SIRCA. Additionally, I exclude all knock-out warrants where strike price and knock-out barrier are not identical. In other words, I exclude all knock-out warrants with an integrated stop-loss barrier.[6]

Archived news data for all underlying stocks is provided by Thomson Reuters NewsScope Content and is tagged through RNSE. News are tagged with sentiment,

[5] A list of all DAX constituents is shown in Table 6.3.

[6] This results in two products with DAX as underlying, and 252 with a DAX constituent as underlying.

relevance and novelty. For more details on the news data set please refer to Section 4.1.3.

6.3.1 Matched Sample

I match buy and sell orders to compute the exact holding period and performance of each trade. I use product identifier (ISIN), timestamp, traded quantity, and routing information of each order as matching criteria. Routing information denotes an integer code that identifies the company that routed the order, i.e. the broker or bank with direct access to the stock exchange. Orders are matched if ISIN, traded quantity, and routing information are identical for the buy and sell order. The time of execution of the sell order needs to succeed the timestamp of the buy order. Due to the large number of products and routing IDs the probability of mismatching orders with the same criteria can be neglected.

I believe that retail investors buying at Stuttgart Stock Exchange are likely to sell there as well. However, there are reasons to sell at Stuttgart Stock Exchange but to buy on an OTC platform, such as intelligent order types (stop-loss, one-cancels-the-other[7]), which are not always available on OTC platforms. Therefore, my algorithm uses buy orders as reference for the matching, i.e. for every buy order in my sample I try to find a matching sell order. Consequently, this might leave some sell orders unmatched.

Several studies have shown the existence of the disposition effect for retail investors. Investors sell winners too early and ride losers too long.[8] Therefore, when trading highly leveraged products it is very likely that no sell orders were submitted to existing buy orders since investors were reluctant to realize their heavy losses and the product might be knocked-out. The position is then erased from investors portfolios and, thus, no sell order exists that could be matched accordingly. To avoid this sample bias, I identify the knock-out date for each product, if there is one. For all buy orders that could not be matched at the first stage, I analyze if there are any

[7]A stop-loss order is an order to sell a security when it touches a defined price. There exist different variations of a stop-loss order, such as a stop-market or stop-limit order. It is designed to protect investors from heavy losses. A one-cancels-the-other order (OCO) is the combination of two orders: A stop order and a limit order. If one of them was executed the other one is canceled automatically.

[8]See Section 3.2 for a more detailed description of the disposition effect.

sell orders for that product with the same routing information between the time of the buy order and the knock-out date. If a sell order exists, independently from the traded quantity, I exclude this buy order from my analysis. If there is not a single sell order in that period with the same routing information, I identify this buy order as a total loss. In total, I am capable of matching roughly 70% of all buy orders in my sample.[9]

For all upcoming tables, I differentiate between knock-out warrants with stock (DAX30 constituent) or index (DAX) as underlying. Panel A always reports results for the first group, whereas panel B shows results for the latter group. For simplicity reasons, I refer to a knock-out warrant with index (stock) as underlying as *index product* (*stock product*). I distinguish between three overall data sets: (i) retail investor trade data, (ii) issuer quote data of knock-out warrants, and (iii) Thomson Reuters news data. Table 6.1 shows descriptive statistics for my trade data set. In total, I combine 291,740 (38,149) trades in index (stock) products, 140,823 (19,631) buy orders and 150,917 (18,518) sell orders, with a total trading volume of EUR 2,270 (151) million. The average trade size is EUR 7,781 (3,970), whereas the median trade size is EUR 1,812 (1,436). I observe that volume in call stock products is almost three times the volume of put stock products. In contrast, volume in put index products is roughly 50% higher than volume in call index products. This opposing effect between the different underlying types has also been shown by Bauer et al. (2009) for plain vanilla options. The higher volume in call stock products compared to put stock products is in line with results reported by Lakonishok et al. (2007). Referring to my subsample for matched trades, mean and median trade sizes are similar to my total sample. Thus, my sample of matched trades seems representative.

Table 6.2 reports descriptive statistics on my quote data set. My sample includes 1,583 different index products and 4,487 stock products from 7 investment banks. Differentiated by option type, I obtain 791 (3,039) call and 792 (1,448) put index (stock) products. At Stuttgart Stock Exchange's request banks are anonymized by relabeling them with characters A to G. Maturity at issuance ranges from 0.15 to 0.62 years for index products and from 0.26 to 0.70 years for stock products. Generally, index products have a shorter total life time than stock products. I define the moneyness

[9] According to my methodological approach I identify 9,454 (5,124) trades in index (stock) products as total losses.

TABLE 6.1: **Descriptive Statistics - Trades.** This table reports descriptive statistics for my trade data sample. My sample includes all customer trades of Stuttgart Stock Exchange for all products shown in Table 6.2 ranging from April 1, 2009 to February 28, 2010. Standard deviations are reported in parantheses.

	All Trades Underlying Type		Matched Sample Underlying Type	
	Stock	Index	Stock	Index
Total Volume [kEUR]	151,449	2,270,105	84,916	1,281,892
Buy Volume [kEUR]	72,620	1,109,062	49,454	664,211
Sell Volume [kEUR]	78,828	1,161,043	35,463	617,681
Call Volume [kEUR]	111,246	899,251	64,304	496,659
Call Buy Volume [kEUR]	54,051	431,896	37,583	256,136
Call Sell Volume [kEUR]	57,195	467,354	26,721	240,523
Put Volume [kEUR]	40,203	1,370,854	20,613	785,233
Put Buy Volume [kEUR]	18,570	677,166	11,871	408,076
Put Sell Volume [kEUR]	21,633	693,688	8,742	377,158
# Trades	38,149	291,740	28,340	190,936
# Buys	19,631	140,823	14,170	95,468
# Sells	18,518	150,917	14,170	95,468
Matching Rate			72.18%	67.79%
Mean Trade Size [EUR]	3,970	7,781	3,490	6,957
	(8,679)	(50,950)	(7,159)	(48,895)
Median Trade Size [EUR]	1,436	1,812	1,476	1,752

TABLE 6.2: **Descriptive Statistics - Quotes.** This table reports descriptive statistics for my quote data sample, starting from April 1st, 2009 until February 28th, 2010. It includes 4,487 (1,583) knock-out warrants with a stock (index) as underlying, issued by seven different investment banks. I report the number of call and put products, mean maturity $(T - t_0)/365$ (where t_0 is the issuance date) in years, and moneyness: S_{t_0}/K for call products and K/S_{t_0} for short products (where K is the strike price and S_{t_0} the index level at issuance). Panel A and B report results differentiated by the underlying type. Standard deviations are reported in parantheses.

Panel A: *stock as underlying*				At Issuance	
Investment Bank	#Products	#Calls	#Puts	Maturity	Moneyness
B	1,261	927	334	0.32	1.16
				(0.17)	(0.14)
D	622	360	262	0.39	1.26
				(0.17)	(0.78)
E	1,264	886	378	0.26	1.18
				(0.13)	(0.17)
F	654	452	202	0.70	1.11
				(0.22)	(0.14)
G	686	414	272	0.62	1.15
				(0.17)	(0.18)
Total	4,487	3,039	1,448	0.41	1.17
				(0.24)	(0.32)

Panel B: *index as underlying*				At Issuance	
Investment Bank	#Products	#Calls	#Puts	Maturity	Moneyness
A	89	51	38	0.15	1.05
				(0.12)	(0.05)
B	522	281	241	0.24	1.05
				(0.18)	(0.05)
C	346	158	188	0.20	1.06
				(0.14)	(0.07)
D	43	15	28	0.62	1.11
				(0.24)	(0.07)
E	291	155	136	0.15	1.06
				(0.07)	(0.07)
F	256	120	136	0.26	1.05
				(0.10)	(0.06)
G	36	11	25	0.21	1.05
				(0.10)	(0.03)
Total	1,583	791	792	0.22	1.06
				(0.16)	(0.06)

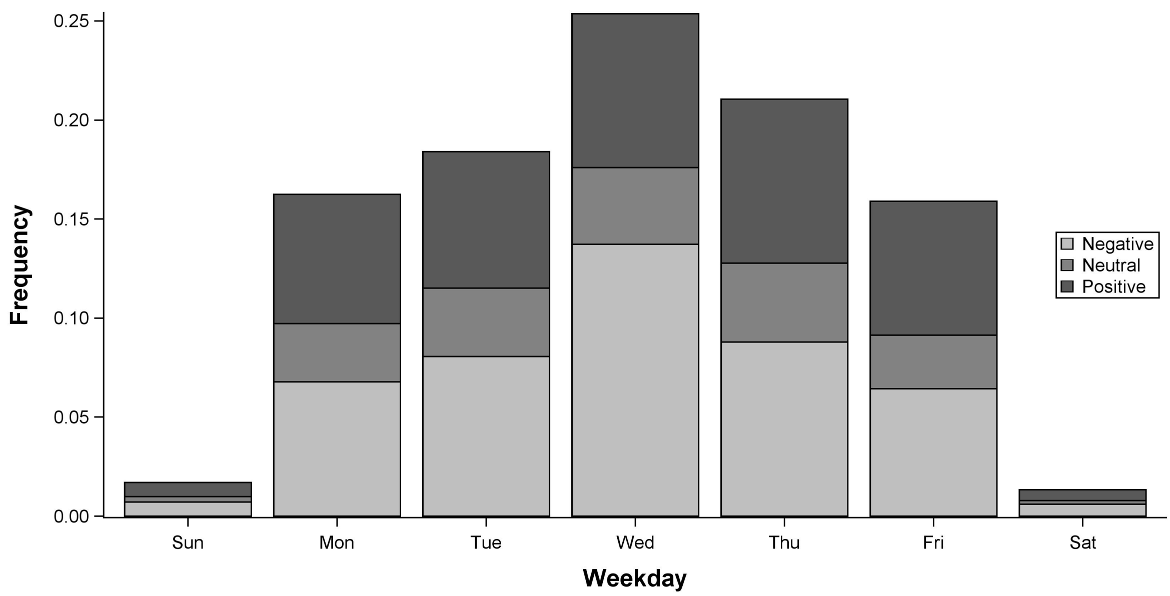

FIGURE 6.1: **News per Weekday on DAX30 Constituents April 2009 to February 2010.** This figure shows the relative share of news messages across all DAX30 constituents per weekday for the period April 2009 to February 2010. News are distinguished along their sentiment: Positive, neutral, or negative.

of a product as S_t/K for call products and K/S_t for put products, where K denotes the strike price and S_t the underlying price at time t. The sample is homogeneous across issuing investment banks with respect to moneyness at issuance, ranging from 1.05 to 1.11 for index products, and 1.11 to 1.26 for stock products. In total, stock products are issued with a higher moneyness and a longer time to maturity compared to index products.

Table 6.3 provides an overview of my third data set: news messages. I incorporate a total of 12,556 news for 31 companies, which consists of 4,697 positive news, 2,195 neutral news, and 5,664 negative news. On average, I observe 405 news per company. Figure 6.1 shows the relative share of news messages for DAX30 constituents per weekday for my sample period. The number of news messages is higher during working days compared to the weekend. At the beginning and end of a working week less news messages hit the market compared to Wednesday, the peak of information arrival.

TABLE 6.3: **Descriptive Statistics - News.** My sample includes 12,556 news messages provided by Thomson Reuters NewsScope Real-time for all DAX30 constituents. News are tagged with data from Thomson Reuters NewsScope Sentiment Engine, which enriches news data with sentiment, affected RIC, and relevance. Sentiment is either positive (+), neutral (0), or negative (-). Standard deviations are reported in parantheses.

Company		News Messages			
RIC	Name	#Total	#+	#0	#-
ADSG.DE	adidas AG	181	75	27	79
ALVG.DE	Allianz SE	421	173	70	178
BASF.DE	BASF AG	299	124	52	123
BAYG.DE	Bayer AG	230	80	39	111
BEIG.DE	Beiersdorf AG	117	50	18	49
BMWG.DE	Bayerische Motoren Werke AG	407	172	79	156
CBKG.DE	Commerzbank	478	149	91	238
DAIGn.DE	Daimler AG	697	269	126	302
DB1Gn.DE	Deutsche Börse AG	923	114	59	750
DBKGn.DE	Deutsche Bank AG	1,720	578	362	780
DPWGn.DE	Deutsche Post AG	234	83	30	121
DTEGn.DE	Deutsche Telekom AG	612	233	92	287
EONGn.DE	E.ON SE	675	279	151	245
FMEG.DE	Fresenius Medical Care AG & Co KGaA	61	36	13	12
FREG_p.DE	Fresenius SE & Co KGaA	54	31	11	12
HNKG_p.DE	Henkel AG & Co. KGaA	137	74	19	44
HNRGn.DE	Hannover Rueckversicherung AG	108	50	11	47
IFXGn.DE	Infineon Technologies AG	273	143	39	91
LHAG.DE	Lufhansa AG	548	160	77	311
LING.DE	Linde AG	101	57	10	34
MANG.DE	MAN SE	221	90	37	94
MEOG.DE	Metro AG	241	95	45	101
MRCG.DE	Merck KGaA	220	74	35	111
MUVGn.DE	Münchner Rückversicherungs-Gesellschaft AG	203	81	28	94
RWEG.DE	RWE AG	616	282	142	192
SAPG.DE	SAP AG	341	152	58	131
SDFG.DE	K+S AG	209	81	20	108
SIEGn.DE	Siemens AG	744	337	137	270
SZGG.DE	Salzgitter AG	111	44	17	50
TKAG.DE	ThyssenKrupp AG	286	114	43	129
VOWG.DE	Volswagen AG	1,088	417	257	414
Total		12,556	4,697	2,195	5,664
Mean		405	152	71	183
		(352.18)	(121.64)	(75.45)	(180.76)
Median		273	114	43	121

6.4 Results

This section presents results for research questions addressed above.

6.4.1 Profitability of Leveraged Trades

My unique data set allows me to study the behavior of the general population of retail investors who trade knock-out warrants since it is not restricted to a certain broker type or bank. If aggregated retail investors trading in knock-out warrants is informed, their trading activity should be profitable on average. In contrast, if investors are uninformed I can expect them to be on the right side of the market in 50% of all trades on average. Hence, this section focuses primarily on the following two research questions:

> **Research Question 2a.** *Are retail investors trading successfully in leverage products?*
>
> **Research Question 2b.** *Which effect do transaction costs have on the performance of retail investors?*

Obviously, retail investors' profession is typically not trading, but they may work for companies that have business relationships with one or more underlying stocks in my sample. This might be a source of private information or a more experienced understanding of a company. Investors with private information would therefore rather buy stock products than index products to isolate all other information which might drive the market. On the other hand, investors with interest in gambling would rather pick index products, since a broader range of barrier levels, as well as higher leverage ratios are available.[10] The leverage ratio of product i measures the sensitivity of the product's price relative to the price of the underlying. The leverage ratio of product i at time t can be computed as follows:

$$Leverage_{it} = \frac{S_{it}}{LP_{it}} c_i, \tag{6.1}$$

[10] In October 2012, 60.4% of all tradable knock-out warrants had an index as underlying, 19.6% a stock, and 15.2% a commodity. Source: German Derivative Association, October Statistic, 2012, http://www.derivateverband.de.

where LP_{it} denotes the price of product i at time t, S_{it} denotes the price of the underlying, and c_i denotes the subscription ratio.[11] The leverage ratio of a product changes continuously, depending on price movements of the underlying. For leverage certificates, a higher leverage ratio is associated with a higher risk of a total loss, since it is more likely that the knock-out barrier will be hit.

I take a two-pronged approach to calculate retail investors profitability: First, I analyze all executed buy orders assuming different fictive holding periods. Second, I calculate the actual performance for a subsample of buy orders that have been matched with existing sell orders as outlined in Section 6.3.1.

Let s_{ij} be the size of trade j in product i, b_{it} the (best) bid price of product i at time t, and f constant (explicit) transaction costs for a single trade, i.e. half a round trip. Let $LP_{it_0(j)}$ be the price at which trade j at time $t_0(j)$ is executed. Let $Ret_{U(i)t_0(j)h}$ be the percentage return of the underlying U of product i for holding period h beginning on trade execution. Let Ret_{ijh} be the percentage raw return of trade j in product i for the holding period h minus the return of the underlying in that period:

$$Ret_{ijh} = \begin{cases} \dfrac{(b_{it_0+h}\, s_{ij} - f) - (LP_{it_0(j)}\, s_{ij} + f)}{LP_{it_0(j)}\, s_{ij} + f} 100 - Ret_{U(i)t_0(j)h}, \\ \qquad \text{if } b_{it_0+h}\, s_{ij} > f \wedge \forall t_0(j) \leq t \leq t_0(j) + h : S_t > X \\ -100 - Ret_{U(i)t_0(j)h}, \text{ else.} \end{cases} \tag{6.2}$$

The condition $b_{it_0+h}\, s_{ij} > f$ denotes the case that an investor does not close his position if transaction costs are higher than the value of his position. In case of a knock-out, the position is automatically eliminated by the broker of the investor without additional costs. I subtract the underlying return to place more weight on the actual choice of leverage. For example, trading with a leverage of one may now result in 0% (correct market anticipation) or -2% (wrong market anticipation) if the underlying increases by 1%. The higher the leverage the more investors are able to outperform the market.

Investors' performance in knock-out warrants is difficult to compare in the cross-section of investors, since leverage ratios and associated risks are different for each

[11] The purpose of the subscription ratio is to scale down the price of a knock-out warrant to an investor-friendly level. The subscription ratio in my sample varies between 0.01 and 1.

trade. Hence, I calculate the risk-adjusted return Ret_{ijh}^{Adj} (sharpe ratio) as

$$Ret_{ijh}^{Adj} = \frac{Ret_{ijh}}{\sigma_i[t_0(j), t_0(j)+h]\, Leverage_{it_0(j)}}, \qquad (6.3)$$

where $\sigma_i[t_0, t_0 + h]$ denotes the standard deviation of the product's underlying between the time of purchase t_0 and the end of the holding period $t_0 + h$.[12] I multiply the standard deviation of the underlying with the current leverage ratio of the product since product prices react accordingly to the leverage ratio larger than the corresponding underlying. A leverage ratio of nine, for example, indicates that the price of the leverage product moves by 9% given a price movement of 1% of the underlying. I assume conservative constant transaction costs of EUR 5 ($f = 5.00$) per trade.[13] Using risk-adjusted returns allows for a better comparability, due to the normalization of raw returns with respect to the risk assumed. Unfortunately, negative returns can therefore not be interpreted meaningfully, because absolute losses are reduced by higher risk.

Additionally, I calculate a performance measure, which does not take into account implicit and explicit transaction costs ($f = 0$). I assume that retail investors are always executed at the midpoint of each quote, thus, I ignore spread costs (implicit transaction costs). This approach enables me to analyze the impact of transaction costs on retail investor performance. In addition to calculating estimates for these measures for several holding periods of all buy orders, I calculate measures for the set of matched trades. Return and standard deviation of product's underlyings used for the performance measures are individually adapted to the holding period of each matched trade.

Table 6.4 reports average performance estimates for both methods and all measures across all observations distinguished by the type of underlying and option type of the knock-out warrant. Entrop et al. (2011) find that the average holding period for knock-out warrants is 1.17 days. For robustness, I calculate returns for holding

[12] Note that sharpe ratio usually refers to σ as the standard deviation of the excess return of the asset. Due to computational reasons I use the underlying standard deviation times the leverage ratio of the knock-out warrant instead of the standard deviation of the knock-out warrant.

[13] As of January 2013, the cheapest German broker (flatex Holding AG, wwww.flatex.de) has round trip costs of at least EUR 10.

periods of 30 min, 1h, 2h, 3h, 4h, 1d, 2d, and 5 days. Holding periods refer to actual trading hours. Periods exceeding trading hours of a day are continued in trading hours on the following day. For example, the performance for the 1h holding period of a trade executed 10 min before the end of the trading period of a day is calculated using the quote 50 min after the opening on the next trading day. I use this trading-hour approach rather than calculating performance for the exact difference in time, since otherwise returns for holding periods less than a day do not change for trades executed towards the end of a day.

I find the performance of retail investors to differ between underlyings. In total, retail investor trades in knock-out warrants with stocks as underlying generate negative raw returns that vary between −4.97% and −9.72% for the different holding periods referring to the buy-and-hold approach. In contrast, trades in index products generate positive raw returns for holding periods greater than four hours. In total raw returns are between −1.79% and 6.95% for all holding periods. The performance of my matched sample does paint an even worse picture. Total raw returns are −29.19% for stock products and −3.28% for index products.

Distinguishing between option types, I find that retail investors trading stock products have a negative performance for both the buy-and-hold approach and the matched sample independently from the option type. For trades in index products I observe a negative performance for trading put products. For call products I only observe a significant positive performance for the buy-and-hold approach for holding periods of at least three hours. Performance of trades in call products based on my matched sample is not significantly different from zero.

However, my performance measure that neglects transaction costs (*w/o TC*) reveals that losses are substantially driven by transaction costs. Comparing estimates of the two performance measures, transaction costs reduce returns by approximately 6% on average. Implicit transaction costs increase with leverage, which will be discussed in more detail in the following section.

When looking at risk-adjusted returns, I observe negative returns for index products for assumed holding periods below four hours. Average sharpe ratios across all trades in index products for all holding periods are below 0.3, which implies a poor risk-adjusted performance. Such low sharpe ratios reflect either unawareness of risk

TABLE 6.4: **Profitability.** This table captures the mean percentage performance based on three different return measures. *Raw Return* denotes the actual return including transaction costs, *Adj. Return* denotes an adapted version of the sharpe ratio, and *w/o TC* captures returns without implicit and explicit transaction costs. All estimates are averaged across all observations for a matched sample and for all buy orders assuming a buy-and-hold strategy for different horizons: 30 minutes, one to four trading hours, and one, two, and five trading days. Periods exceeding trading hours of a day are continued at trading hours on the following day. Results are differentiated by the type of underlying: Stock or index. T-values are reported in parantheses. */**/*** denotes significance below the 5%/1%, and 0.1% level, respectively.

Panel A: *stock as underlying*

	Matched	Buy-and-Hold							
	Sample	0.5h	1h	2h	3h	4h	1d	2d	5d
Raw Return									
Total	-29.19***	-4.97***	-5.21***	-5.23***	-5.55***	-6.07***	-8.19***	-9.72***	-6.68***
	(-50.66)	(-51.73)	(-45.56)	(-38.92)	(-34.97)	(-34.64)	(-31.20)	(-30.48)	(-16.35)
Call	-33.55***	-4.41***	-4.77***	-4.86***	-5.21***	-5.65***	-7.84***	-9.65***	-6.87***
	(-53.95)	(-38.55)	(-34.87)	(-30.17)	(-26.77)	(-26.87)	(-24.77)	(-24.61)	(-13.93)
Put	-19.12***	-6.24***	-6.21***	-6.07***	-6.30***	-7.03***	-8.98***	-9.90***	-6.24***
	(-15.43)	(-35.44)	(-29.82)	(-24.91)	(-23.22)	(-22.16)	(-19.12)	(-18.14)	(-8.57)
w/o TC									
Total	-24.71***	2.03***	1.71***	1.63***	1.10***	0.50*	-1.88***	-3.70***	-0.83
	(-40.05)	(15.72)	(12.57)	(10.48)	(5.09)	(2.24)	(-6.15)	(-9.90)	(-1.73)
Call	-29.65***	2.29***	1.83***	1.66***	1.03***	0.51	-1.91***	-4.07***	-1.51*
	(-44.82)	(13.94)	(10.94)	(8.81)	(3.67)	(1.84)	(-5.11)	(-8.70)	(-2.54)
Put	-13.34***	1.43***	1.44***	1.55***	1.26***	0.46	-1.80***	-2.86***	0.69
	(-9.97)	(7.29)	(6.22)	(5.67)	(4.10)	(1.30)	(-3.43)	(-4.73)	(0.84)
Adj. Return									
Total	-1.41	-4.16***	-2.99***	-2.23***	-1.89***	-1.77***	-1.01***	-1.04***	-0.58***
	(-0.54)	(-33.50)	(-32.38)	(-27.73)	(-26.15)	(-28.10)	(-26.31)	(-26.70)	(-16.69)
Call	1.39	-3.16***	-2.46***	-1.91***	-1.64***	-1.49***	-0.86***	-0.88***	-0.61***
	(0.75)	(-35.98)	(-26.52)	(-19.46)	(-22.15)	(-23.72)	(-21.11)	(-22.17)	(-15.80)
Put	-7.22	-6.41***	-4.19***	-2.94***	-2.46***	-2.41***	-1.37***	-1.39***	-0.50***
	(-1.04)	(-18.29)	(-19.48)	(-21.21)	(-14.82)	(-16.23)	(-15.99)	(-15.60)	(-7.07)

continued on the next page…

TABLE 6.4: continued.

Panel B: *index as underlying*	Matched Sample	Buy-and-Hold 0.5h	1h	2h	3h	4h	1d	2d	5d
Raw Return									
Total	-3.28***	-1.79***	-1.23***	-0.55***	-0.06	0.31**	2.81***	4.48***	6.95***
	(-16.31)	(-39.23)	(-19.21)	(-6.82)	(-0.59)	(2.87)	(16.85)	(19.38)	(21.65)
Call	0.02	-1.85***	-1.00***	0.04	0.62***	1.54***	5.66***	10.48***	18.84***
	(0.08)	(-25.12)	(-9.30)	(0.34)	(4.08)	(8.75)	(21.23)	(29.01)	(35.16)
Put	-5.65***	-1.75***	-1.40***	-0.98***	-0.54***	-0.58***	0.75***	0.14	-1.54***
	(-21.07)	(-30.19)	(-17.82)	(-9.54)	(-4.45)	(-4.26)	(3.51)	(0.46)	(-3.92)
w/o TC									
Total	-1.98***	-0.35***	0.21**	0.88***	1.38***	1.73***	4.20***	5.81***	8.22***
	(-9.64)	(-7.52)	(3.21)	(10.71)	(14.20)	(15.71)	(24.64)	(24.71)	(25.17)
Call	1.45***	-0.36***	0.50***	1.53***	2.09***	3.02***	7.14***	11.96***	20.33***
	(4.69)	(-4.86)	(4.50)	(11.51)	(13.59)	(16.77)	(26.17)	(32.42)	(37.19)
Put	-4.44***	-0.34***	0.01	0.42***	0.86***	0.80***	2.06***	1.37***	-0.42
	(-16.26)	(-5.74)	(0.06)	(4.00)	(6.90)	(5.81)	(9.49)	(4.50)	(-1.07)
Adj. Return									
Total	-0.31	-0.73***	-0.58***	-0.42***	-0.28***	-0.20***	0.02*	-0.01	0.24***
	(-0.87)	(-31.82)	(-36.94)	(-25.45)	(-17.37)	(-13.36)	(2.15)	(-0.65)	(19.25)
Call	0.26	-0.72***	-0.52***	-0.22***	-0.27***	-0.18***	0.10***	0.11***	0.18***
	(0.88)	(-31.95)	(-22.01)	(-9.40)	(-11.51)	(-8.40)	(6.74)	(7.63)	(9.66)
Put	-0.71	-0.74***	-0.63***	-0.56***	-0.28***	-0.21***	-0.03*	-0.09***	0.29***
	(-1.24)	(-20.51)	(-29.71)	(-24.70)	(-13.05)	(-10.40)	(-2.31)	(-6.46)	(16.83)

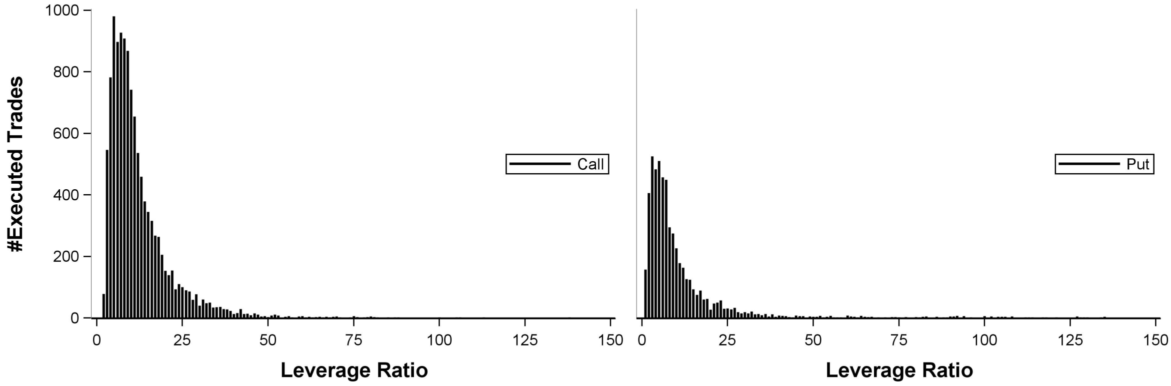

FIGURE 6.2: **Risk-Habitat - Stock.** All figures visualize the number of executed buy orders in knock-out warrants by retail investors with respect to the traded leverage ratio. X-axis shows the leverage ratio and y-axis shows the number of orders. The left chart visualizes the number of call positions and the right chart number of put positions.

by retail investors, or a strong desire for high leverage ratios that dominates the associated risk. Risk-adjusted returns for stock products are negative for all analyzed scenarios.

6.4.2 Leverage, Volume, and Order Type

Which characteristics influence the profitability of retail investors' leveraged trades? To answer this question, I study returns with respect to trading volume, leverage ratio, and order type. Better informed investors might trade with higher volume or leverage ratio to increase their expected profit. Figure 6.2 and 6.3 visualize the number of trades with respect to the taken risk differentiated for stock and index products, respectively. The average traded leverage ratio is higher for index products than for stock products. I observe that most trades are executed at leverage ratios between 5 and 60 for index products and between 1 and 20 for stock products. Both distributions are skewed towards high leverage ratios and are not substantially different between option types. In other words, retail investors are willing to face the same risk when entering long or short positions in the underlying, but they face higher risks when trading index products compared to stock products.

Figure 6.4 illustrates the invested capital of retail investors. Most orders are

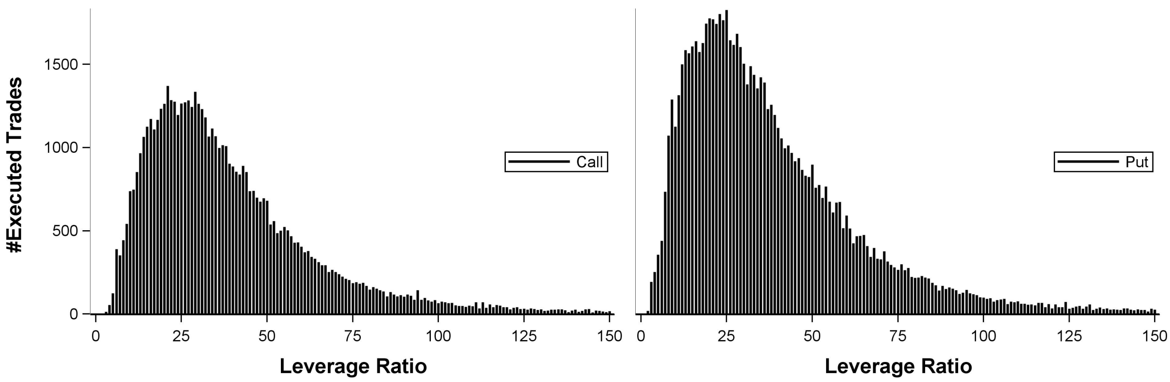

FIGURE 6.3: **Risk-Habitat - Index.** All figures visualize the number of executed buy orders in knock-out warrants by retail investors with respect to the traded leverage ratio. X-axis shows the leverage ratio and y-axis shows the number of orders. The left chart visualizes the number of call positions and the right chart number of put positions.

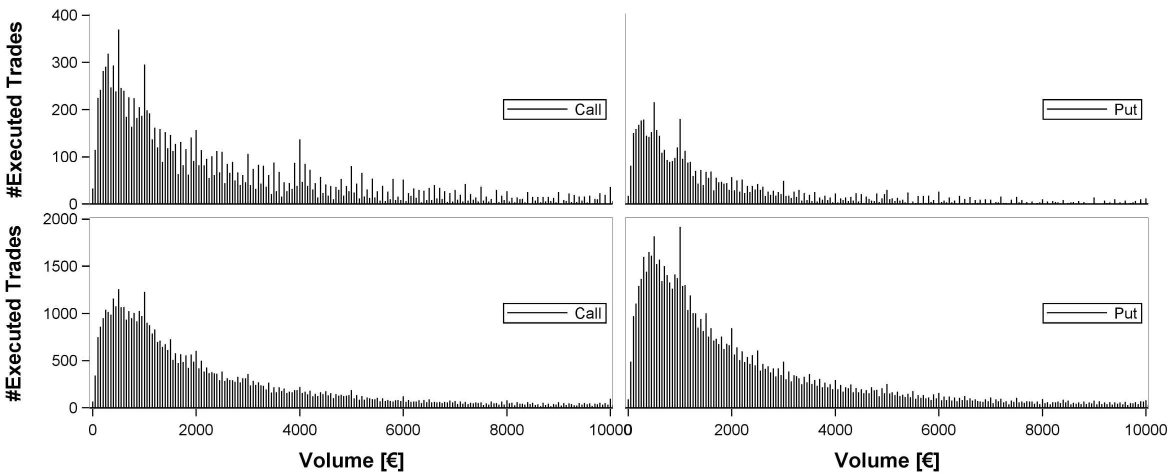

FIGURE 6.4: **Invested Capital.** All figures visualize the frequency of executed buy orders in knock-out warrants by retail investors with respect to the invested volume (price $\times$ size). X-axis shows the leverage ratio and y-axis shows the frequency. The upper figures visualize this relationship for knock-out warrants with stocks as underlying, whereas the lower figures show the case for index as underlying.

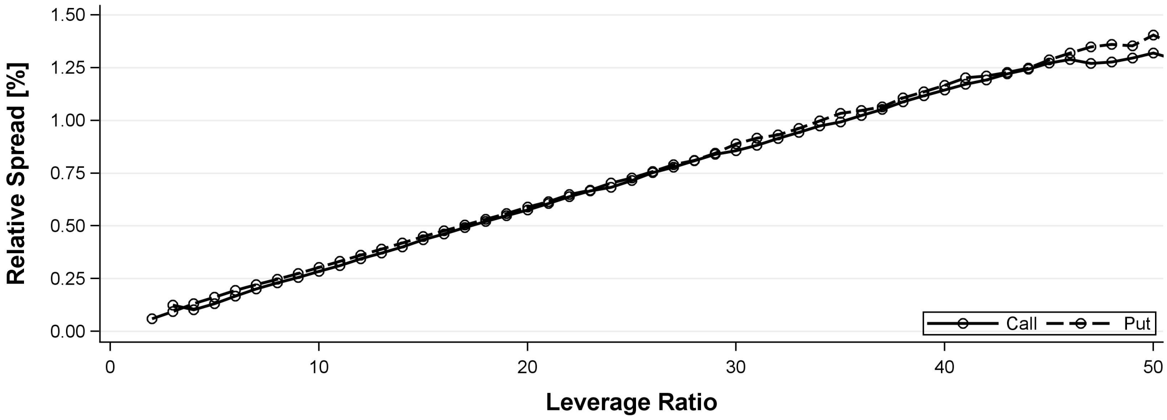

FIGURE 6.5: **Leverage and Relative Spread.** This figure visualizes the dependency of leverage ratio and the relative spread. X-axis shows the leverage ratio, and y-axis shows the average relative spread across all products.

smaller than EUR 5,000 with a great part residing below the threshold of EUR 1,000. Combining those results for small invested capital and high leverage ratios brings to mind the character of a lottery ticket: Small costs but high potential profits. Table 6.5 shows average performance estimates analogous to the prior section but differentiated by leverage ratio terciles.

For both stock and index products, I observe a negative performance for retail investors trading with medium or low leverage ratios for all considered holding periods as well as for my matched sample. Interestingly, for highly leveraged trades in index products, I observe a positive performance whereas for trades with high leverage ratios in stock products, I observe the highest relative losses.

Figure 6.5 shows the relationship of leverage ratio and the average relative spread across all products. Since there is a linear relationship between relative spread and leverage ratio, implicit costs increase with taken risk.

Looking at the profitability results for highly leveraged trades, the difference between my raw return measure, including explicit and implicit transaction costs, and the measure without both shows that negative returns for stock products are mostly driven by transaction costs. Ignoring higher implicit costs supports the hypothesis that retail investors are either ignorant or trade for entertainment. Nevertheless, risk-adjusted returns show that no matter at which point in time capital is invested in knock-out warrants, on average, it is always a poor investment with respect to the risk incurred.

In the following, I analyze the profitability of trades in more detail with respect to other order characteristics. Kelley and Tetlock (2012) analyze retail investor performance with respect to the order type and find that only market orders predict "the tone of news". I define an order as marketable if it is executed within one second after submission. All other orders are labeled limit orders. Let $Volume_{ij}$ denote the number of shares bought times buy price ($LP_{it_0(j)}\, s_{ij}$), and $Leverage_{it_0(j)}$ be the leverage ratio of buy order j. I standardize[14] both variables prior to analysis to improve comparability of the influencing factors. I run the following regression model across all observations[15]:

$$\begin{aligned} Ret_{ijh} = \alpha &+ \beta_1\, Leverage_{it_0(j)} + \beta_2\, Volume_{ij} \\ &+ \beta_3\, D^{Limit}_{ij} + \beta_4\, D^{Call}_{ij} + \epsilon_j, \end{aligned} \tag{6.4}$$

where D^{Limit}_{ij} denotes a dummy variable set to one if the order is a limit order and zero otherwise; D^{Call}_{ij} is a dummy variable indicating a call ($=1$) or put ($=0$) product. I run the regression separately for each assumed holding period and the matched sample. Table 6.6 reports results for the above regression model for stock products (Panel A) and for index products (Panel B).

I observe that investors, who trade products with higher leverage ratios, are more successful than others for holding periods exceeding two hours. The performance of large trades varies between underlying types. Larger trades in stock products are on average more successful, whereas the opposite holds for index products. For holding periods up to four hours, I observe for both underlying types that investors, who use market orders, generate higher returns than those who use limit orders. For trades in stock products, this relationship holds for all holding periods. Market orders indicate that investors are interested in fast execution, which might be an indicator of more informed trading compared to investors using limit orders (Harris, 2003).[16] How-

[14] I standardize a variable in the following way: $var = (variable - \overline{variable})/\mathrm{STD}(variable)$.

[15] My results are robust if I exclude individual variables from the model. Additionally, an interaction effect of volume and leverage is not significant. Using a truncated regression model or a logit model instead of my standard regression model does not change the effects. Transformation ($(Ret_{ijh})^3$) of raw returns also has no effect on the direction of the estimated coefficients.

[16] Traditional literature focuses on market vs. limit orders from a market microstructure perspective. Results retrieved are only of limited use in the market for structured products since there is a

TABLE 6.5: **Profitability of Leveraged Trades.** This table captures the mean percentage performance based on three different return measures. *Raw Return* denotes the actual return including transaction costs, *Adj. Return* denotes an adapted version of the sharpe ratio, and *w/o TC* captures returns without implicit and explicit transaction costs. All estimates are averaged across all observations for a matched sample and for all buy orders assuming a buy-and-hold strategy for different horizons: 30 minutes, one to four trading hours, and one, two, and five trading days. I cluster investor trades by terciles of traded leverage ratios. Periods exceeding trading hours of a day are continued at trading hours on the following day. Results are differentiated by the type of underlying: Stock (panel A) or index (panel B). T-values are reported in parentheses. */**/*** denotes significance below the 5%/1%, and 0.1% level, respectively.

Panel A: *stock as underlying*

	Matched Sample	Buy-and-Hold 0.5h	1h	2h	3h	4h	1d	2d	5d
Raw Return									
High Leverage	-39.52***	-6.45***	-6.75***	-6.93***	-7.15***	-7.71***	-10.14***	-11.80***	-7.17***
	(-26.28)	(-28.19)	(-25.03)	(-21.43)	(-18.35)	(-18.51)	(-16.34)	(-15.56)	(-7.26)
Medium Leverage	-40.96***	-4.48***	-4.68***	-4.57***	-5.00***	-5.50***	-7.97***	-9.63***	-5.43***
	(-15.66)	(-34.04)	(-29.02)	(-25.18)	(-23.97)	(-22.58)	(-20.44)	(-20.37)	(-8.71)
Low Leverage	-26.15***	-3.94***	-4.17***	-4.16***	-4.47***	-4.98***	-6.45***	-7.78***	-7.43***
	(-41.26)	(-36.73)	(-32.05)	(-27.67)	(-26.65)	(-24.87)	(-22.56)	(-22.17)	(-17.16)
w/o TC									
High Leverage	-35.05***	3.53***	3.03***	2.67***	1.92***	1.18*	-1.62*	-3.86***	0.29
	(-21.26)	(10.38)	(8.82)	(6.80)	(3.30)	(2.05)	(-2.13)	(-4.11)	(0.24)
Medium Leverage	-33.46***	1.84***	1.64***	1.75***	1.27***	0.73**	-2.01***	-3.83***	0.45
	(-11.45)	(13.79)	(9.83)	(9.22)	(5.84)	(2.87)	(-4.89)	(-7.65)	(0.68)
Low Leverage	-21.96***	0.66***	0.43**	0.44**	0.10	-0.43*	-1.99***	-3.41***	-3.14***
	(-32.67)	(6.16)	(3.25)	(2.90)	(0.61)	(-2.10)	(-6.73)	(-9.32)	(-6.94)
Adj. Returns									
High Leverage	-0.18*	-2.50***	-1.83***	-1.31***	-1.09***	-0.97***	-0.59***	-0.62***	-0.26***
	(-2.29)	(-19.79)	(-19.78)	(-16.16)	(-11.54)	(-12.04)	(-11.58)	(-10.82)	(-4.47)
Medium Leverage	-1.82*	-3.27***	-2.45***	-1.83***	-1.68***	-1.59***	-0.95***	-0.95***	-0.51***
	(-2.53)	(-27.28)	(-19.59)	(-20.74)	(-18.44)	(-19.21)	(-16.12)	(-15.03)	(-9.46)
Low Leverage	-1.54	-6.20***	-4.32***	-3.24***	-2.65***	-2.50***	-1.36***	-1.39***	-0.83***
	(-0.49)	(-20.81)	(-21.27)	(-17.27)	(-16.75)	(-18.36)	(-17.75)	-(19.39)	(-13.26)

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TABLE 6.5: continued.

Panel B: *index as underlying*	Matched	Buy-and-Hold							
	Sample	0.5h	1h	2h	3h	4h	1d	2d	5d
Raw Return									
High Leverage	2.87***	-2.35***	-0.49**	1.66***	3.55***	5.16***	11.47***	15.23***	21.30***
	(6.56)	(-19.52)	(-2.85)	(7.70)	(14.07)	(17.95)	(26.02)	(25.71)	(26.96)
Medium Leverage	-4.26***	-1.76***	-1.86***	-1.72***	-1.94***	-2.12***	-0.62**	0.99**	4.10***
	(-16.22)	(-33.35)	(-25.35)	(-18.06)	(-17.05)	(-16.17)	(-2.97)	(3.26)	(9.00)
Low Leverage	-10.48***	-1.26***	-1.36***	-1.58***	-1.74***	-2.02***	-2.27***	-2.92**	-4.96***
	(-39.30)	(-35.82)	(-28.16)	(-27.76)	(-26.01)	(-26.26)	(-19.43)	(-17.42)	(-18.96)
w/o TC									
High Leverage	4.94***	0.01	1.88***	4.00***	5.91***	7.50***	13.70***	17.35***	23.32***
	(1104)	(0.04)	(10.72)	(18.11)	(22.78)	(25.42)	(30.38)	(28.66)	(28.93)
Medium Leverage	-3.24***	-0.57***	-0.67***	-0.53***	-0.75***	-0.94***	0.54*	2.11***	5.14***
	(-12.23)	(-10.89)	(-9.16)	(-5.53)	(-6.59)	(-7.12)	(2.56)	(6.91)	(11.18)
Low Leverage	-9.85***	-0.49***	-0.59***	-0.81***	-0.97***	-1.25***	-1.50***	-2.15***	-4.23***
	(-36.44)	(-13.91)	(-12.09)	(-14.18)	(-14.42)	(-16.17)	(-12.80)	(-12.72)	(-16.09)
Adj. Returns									
High Leverage	-0.78	-0.45***	-0.32***	-0.09**	0.13***	0.22***	0.41***	0.33***	0.58***
	(-0.85)	(-17.88)	(-12.62)	(-3.22)	(4.86)	(9.17)	(25.88)	(21.80)	(31.19)
Medium Leverage	-0.08	-0.72***	-0.62***	-0.44***	-0.36***	-0.30***	-0.03	0.01	0.35***
	(-0.20)	(-26.94)	(-23.12)	(-15.75)	(-13.56)	(-12.11)	(-1.69)	(0.49)	(15.98)
Low Leverage	-0.03	-1.04***	-0.82***	-0.73***	-0.59***	-0.51***	-0.31***	-0.36***	-0.20***
	(-0.20)	(-17.58)	(-27.22)	(-24.72)	(-19.83)	(-18.06)	(-15.89)	(-17.82)	(-7.82)

TABLE 6.6: **Volume, Leverage and Order Type.** This table reports results for the regression model measuring the influence of volume, leverage, and order type on the raw relative return of retail investors. I define an order as marketable if it is executed within one second after submission. All other orders are labeled limit orders. Let $Volume_j$ denote the number of shares bought times buy price, and $Leverage_{it_0(j)}$ be the leverage ratio of buy order j. *Leverage* and *Volume* variables are standardized. Performance is measured two-fold: (i) based on a matched subsample and (ii) for the total sample, assuming a buy-and-hold strategy for different horizons: 30 minutes, one to four trading hours, and one, two, and five trading days. Periods exceeding trading hours of a day are continued at trading hours on the following day. I run the regression separately for each assumed holding period and the matched sample. Results are differentiated by the type of underlying: Panel A for products with stock as underlying, and Panel B for products with index as underlying. T-values are reported in parentheses. */**/*** denotes significance below the 5%/1%, and 0.1% level, respectively.

Panel A: *stock as underlying*

	Matched	Buy-and-Hold							
	Sample	0.5h	1h	2h	3h	4h	1d	2d	5d
Intercept	-56.57***	-3.96***	-4.21***	-4.44***	-4.43***	-4.83***	-6.39***	-6.59***	-2.48
	(-30.10)	(-13.23)	(-11.78)	(-10.56)	(-8.94)	(-8.80)	(-7.77)	(-6.60)	(-1.93)
Leverage	-2.84***	-0.16	-0.54***	-0.81***	1.14***	0.54**	0.10	1.15***	2.33***
	(-7.00)	(-1.62)	(-4.71)	(-5.96)	(7.07)	(3.08)	(0.40)	(3.63)	(5.50)
Volume	17.38***	0.86***	0.81***	0.81***	0.98***	1.14***	1.24***	1.59***	1.83***
	(4.80)	(8.81)	(7.00)	(5.77)	(6.11)	(6.50)	(4.66)	(4.91)	(4.44)
Limit Order	44.65***	-2.62***	-2.30***	-1.88***	-2.06***	-2.47***	-2.93***	-3.70***	-4.13***
	(24.70)	(-9.05)	(-6.67)	(-4.62)	(-4.31)	(-4.66)	(-3.69)	(-3.83)	(-3.32)
Call	-15.23***	1.83***	1.46***	1.22***	0.99**	1.29***	1.09	0.13	-0.86
	(-12.45)	(8.83)	(5.89)	(4.18)	(2.86)	(3.40)	(1.91)	(0.19)	(-0.97)

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TABLE 6.6: continued.

Panel B: *index as underlying*	Matched Sample	Buy-and-Hold 0.5h	1h	2h	3h	4h	1d	2d	5d
Intercept	-18.16***	-1.06***	-0.72***	-0.52*	0.27	-0.26	-1.90***	-7.75***	-12.19***
	(-23.60)	(-7.34)	(-3.54)	(-2.03)	(0.90)	(-0.76)	(-3.59)	(-10.64)	(-12.08)
Leverage	-1.73***	-0.34***	1.52***	2.56***	3.70***	4.02***	2.82***	4.05***	5.15***
	(-8.03)	(-6.20)	(19.88)	(26.18)	(32.24)	(30.73)	(16.74)	(17.77)	(16.27)
Volume	-0.47*	0.03	0.01	-0.14	-0.19*	-0.23*	-0.71***	-0.88***	-0.98**
	(-2.50)	(0.69)	(0.17)	(-1.70)	(-2.05)	(-2.16)	(-4.30)	(-3.87)	(-3.08)
Limit Order	13.31***	-0.75***	-0.72***	-0.43	-0.79**	-0.22	2.98***	8.70***	11.89***
	(17.17)	(-5.10)	(-3.53)	(-1.67)	(-2.61)	(-0.63)	(5.59)	(11.84)	(11.66)
Call	5.84***	-0.15	0.37**	0.99***	1.13***	2.10***	5.00***	10.65***	20.65***
	(14.42)	(-1.61)	(2.87)	(6.09)	(5.91)	(9.65)	(14.77)	(22.83)	(31.79)

ever, loadings for the matched sample show contradicting results and thus makes it impossible to derive a final conclusion on the matter of order types. Investors trading call products have a better performance on average than those trading put products. I attribute this difference to the bullish market development during my sample period.

6.4.3 News Trading

Retail investors seem to perform badly when trading stock products. To provide more detailed insights, I analyze retail investors entered positions in knock-out warrants around news announcements. This objective has been facilitated in the following research question:

Research Question 2c. *How do retail investors react to new information?*

Figure 6.6 visualizes the number of executed buy orders in stock products and the corresponding number of news announcements across all underlyings in my sample. It seems that investors trade more intensively around news announcements. Barber and Odean (2008) find that retail investors react to news on spot markets and pick attention-grabbing stocks. I analyze retail investors' trading intensity around news through the following regression model. I aggregate all executed buy orders on a minute basis and calculate the number of trades, trading volume, and entered long and short positions in the underlying. I build intervals I_1, I_2, and I_3 for different periods before and after news, similar to Riordan et al. (2013):

$$I_{nt} = \begin{cases} 1 & n = 1 : \text{if } t \text{ is 6 hours before a news} \\ & n = 2 : \text{if } t \text{ is 6 hours after a news} \\ 0 & \text{else.} \end{cases}$$

I use those dummy variables to test whether trading activity increases around news. I use six hour periods around news to account for a possibly delayed reaction of retail investors to news which might occur due to regular job duties for example. I build

guaranteed execution at the current best bid and best ask price for volume up to EUR 20,000. For stock markets Anand et al. (2005) argue that informed investors, are using both limit and market orders. For a more detailed overview refer to Section 3.2.

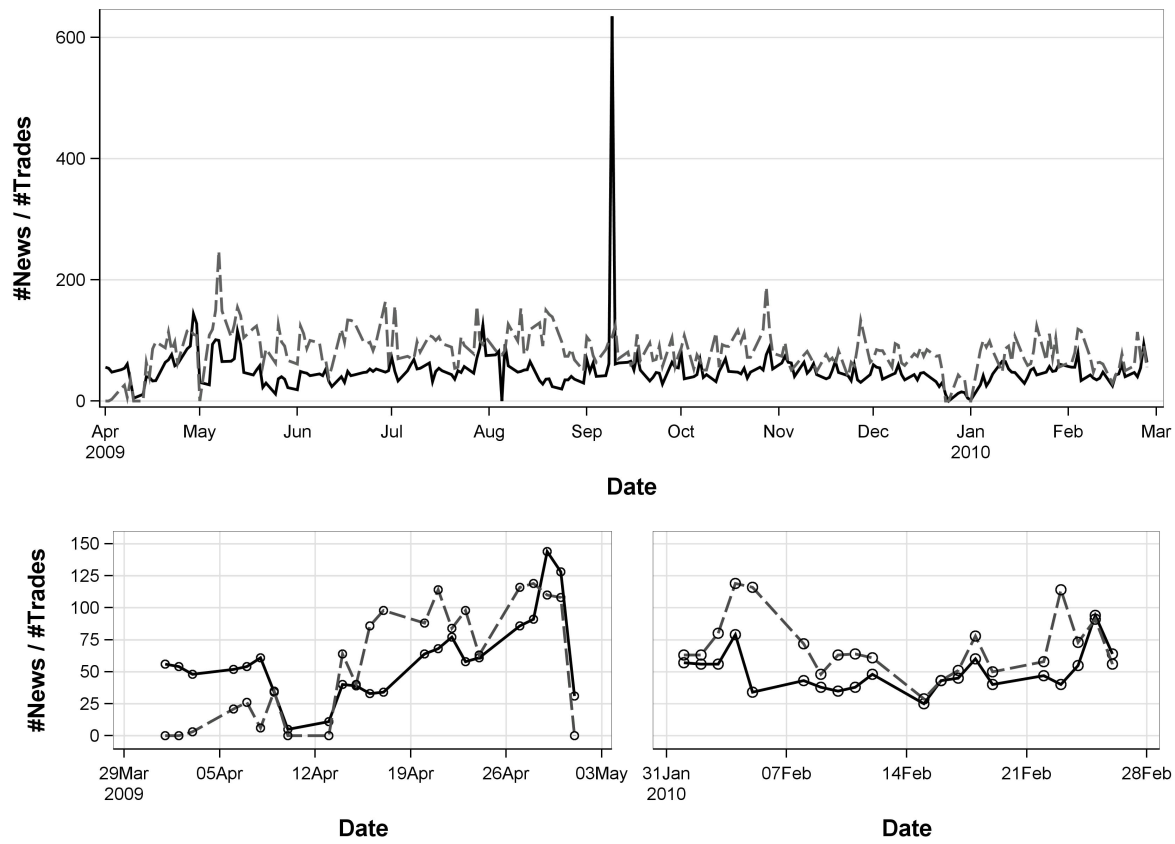

FIGURE 6.6: **News and Trades.** These figures visualize the total number of news for all underlyings and trades in knock-out warrants with a stock as underlying. X-axis shows the date, and y-axis denotes the number of news and trades occurring on the individual day. The gray dashed line denotes the number of trades, and the black line denotes the number of news. The lower figures show snapshots of the sample for April 2009 and February 2010, respectively.

sentiment dummy variables S_{mt} separately for positive ($m = 1$), negative ($m = 2$), and neutral ($m = 3$) news announcements. They are set to one within a range of six hours around a positive, negative, and neutral news event, respectively. Let l denote an observation in my data set, and x denotes the underlying of the product the observation belongs to. I include dummy variables for the underlying (U), for the hour of the day (T), and the day of the week (W). Let M_{xl} denote the trading intensity measure (#Trades, Volume, #Long, #Short) for underlying x and observation l. The regression is then modeled as follows:

$$M_{xl} = \alpha + \sum_{n=1}^{2} \sum_{m=1}^{3} \psi_{nm} I_{nxl} S_{mxl} + \sum_{x=1}^{30} \upsilon_x U_x + \sum_{t=1}^{11} \tau_t T_t + \sum_{d=1}^{4} \omega_d W_d + \epsilon_x.$$

I use generalized method of moments (GMM) for the estimation and correct standard errors for heteroscedasticity effects, and serial correlation using the procedure proposed by Newey and West (1987). Consequently, I obtain results for the trading intensity six hours before and after news, relative to periods of no news, and with respect to the sentiment of news.

Table 6.7 reports results for the above regression model, excluding all control variables for clarity reasons. As already indicated by Figure 6.6, the number of trades in knock-out warrants is higher around news events of the underlying. This is in line with research on ordinary stocks by Riordan et al. (2013), and Berry and Howe (1994). Overall, I observe positive estimates for all trading intensity measures - ignoring the net trading measure - around news, except for trading volume before neutral news. This means that overall trading activity increases around news. The increase in entered short positions compared to long positions seems to be higher before positive and neutral news, and lower before negative news. However, the difference of long minus short positions before positive news and before negative news is not significant (estimate: 1.97; t-value: 0.58).

To calculate the actual profitability around news events, I calculate for each trade the difference in time to the next news after the trade that refers to the specific underlying stock. I cluster trades by the passing time until the next news event occurs. I group trades that have been executed within 30 minutes before a news event in the underlying, between 30 minutes and one hour, one hour and five hours, and between

TABLE 6.7: **Retail Investor Trading Intensity Around News.** This table provides results for trading intensity measures around news for retail investors. The terms *Positive, Negative*, and *Neutral* refer to the sentiment analysis of the Reuters NewsScope Sentiment Engine. *Before* and *After* denote the period of six hours before and after individual news. T-values are reported in parentheses. */**/*** denotes significance below the 5%/1%, and 0.1% level, respectively.

	Positive		Negative		Neutral	
	Before	After	Before	After	Before	After
#Trades per Min. [× 10k]	9.79***	7.48***	12.27***	12.39***	4.76**	9.68***
	(6.50)	(5.39)	(9.25)	(9.64)	(2.68)	(5.16)
Volume per Min.	2.49*	0.23	4.39***	4.22***	-1.99	3.90*
	(2.24)	(0.23)	(3.76)	(3.74)	(-1.32)	(2.25)
#Long Positions per Min. [× 10k]	4.65***	5.02***	7.30***	6.19***	0.41	6.99***
	(4.50)	(4.84)	(6.86)	(6.19)	(0.28)	(4.51)
#Short Positions per Min. [× 10k]	5.14***	2.46**	4.98***	6.20***	4.35***	2.70**
	(4.74)	(2.70)	(6.40)	(7.83)	(4.24)	(2.59)
#Long - #Short Positions per Min [× 10k]	-0.50	2.56	2.32	-0.01	-3.90*	4.29*
	(-0.33)	(1.87)	(1.78)	(-0.01)	(-2.24)	(2.31)

five hours and 24 hours. Table 6.8 reports results for the predictive capabilities of retail investor trades. I exclude all combinations of holding periods and time differences which would refer to a sell of the position before the time of arrival of the actual predicted news. Retail investors have a negative performance at all times, which implies that informational advantages can be ruled out as trading motivation. Raw returns range from -5.04% to -12.40% for the buy-and-hold approach, and from -24.38% to -29.15% for my matched sample. Again, transaction costs are causing negative performance to a large extent.

Summarizing, retail investors are attracted by news events, but have no informational advantage whatsoever. Due to the leverage of the analyzed products, they lose substantial amounts of money within a short period of time. Barber and Odean (2000) argue that such behavior of increased trading activity but poor performance can be explained through overconfidence of retail investors (see Section 3.2). Another alternative explanation is the existence of the disposition effect (see Section 3.2). In case of knock-out warrants, the disposition effect could lead to higher losses compared to stock investments. Investors that are reluctant to realize their losses, which might even occur within hours or minutes, might suffer from a total loss in the end. Additionally, the higher leverage of products could lead to a higher misjudgment of probabilities. As a result, investors could be more optimistic regarding the future returns and, thus, refuse to realize losses. Furthermore, prices of knock-out warrants very close to the barrier are very small, which might result in an additional gambling effect in the way of "all-or-nothing" for investors. They rather have the chance of a turn around and, thus, higher profits than to save the residual amount of their investment.

6.5 Conclusion

> *Investing should be more like watching paint dry or watching grass grow. If you want excitement, take $800 and go to Las Vegas.*
>
> - Paul Samuelson, Nobel laureate

Several studies have shown that retail investors trade excessively and tend to favor stocks with lottery-like characteristics (for example: Han and Kumar, 2012; Brunner-

TABLE 6.8: **News Trading.** I analyze for each trade the difference in time to the next news ahead. Reported values are the mean relative performance [%] (*Raw Ret.* and *w/o TC*) and sharpe ratio (*Adj. Ret.*) [%] across all trades differentiated by their distance in time to the news after (*Prediction*) the trade. Performance is measured based on a matched sample as well as assuming a buy-and-hold strategy for different horizons: 30 minutes, one to four trading hours, and one, two, and five trading days. Periods exceeding trading hours of a day are continued at trading hours on the following day. T-values are reported in parantheses. */**/*** denotes significance below the 5%/1%, and 0.1% level, respectively.

	Matched Sample	Buy-and-Hold 0.5h	1h	2h	3h	4h	1d	2d	5d
Raw Return									
$t < 0.5h$	-26.11***	-5.40***	-5.55***	-5.88***	-6.64***	-7.49***	-9.47***	-11.39***	-9.29***
	(-13.80)	(-17.18)	(-15.08)	(-13.45)	(-13.76)	(-14.37)	(-12.05)	(-12.37)	(-8.34)
$0.5h \leq t < 1h$	-29.15***		-5.94***	-6.21***	-7.04***	-8.18***	-11.53***	-12.40***	-10.33***
	(-13.09)		(-12.38)	(-11.57)	(-11.53)	(-11.16)	(-10.80)	(-9.96)	(-6.70)
$1h \leq t < 5h$	-24.38***			-5.04***	-5.82***	-6.74***	-9.44***	-10.12***	-7.18***
	(-19.04)			(-18.82)	(-18.66)	(-19.04)	(-17.15)	(-14.94)	(-8.37)
$5h \leq t < 24h$	-28.72***						-6.32***	-9.18***	-6.10***
	(-27.42)						(-12.88)	(-15.62)	(-8.19)
w/o TC									
$t < 0.5h$	-21.26***	1.69***	1.48***	1.06*	0.19	-0.87	-3.02***	-5.14***	-3.03*
	(-10.38)	(4.58)	(3.42)	(2.07)	(0.35)	(-1.53)	(-3.44)	(-5.03)	(-2.38)
$0.5h \leq t < 1h$	-24.63***		0.91	0.53	-0.42	-1.93*	-5.57***	-6.47***	-4.75**
	(-10.40)		(1.74)	(0.91)	(-0.63)	(-2.47)	(-4.85)	(-4.83)	(-2.86)
$1h \leq t < 5h$	-19.75***			1.59***	0.69*	-0.36	-3.44***	-4.30***	-1.36
	(-14.39)			(5.27)	(2.01)	(-0.93)	(-5.71)	(-5.84)	(-1.46)
$5h \leq t < 24h$	-24.18***						0.36	-2.88***	0.00
	(-21.57)						(0.64)	(-4.44)	(0.00)
Adj. Returns									
$t < 0.5h$	0.22	-4.02***	-3.15***	-2.56***	-2.14***	-1.75***	-1.19***	-1.36***	-0.68***
	(0.44)	(-12.67)	(-11.86)	(-14.14)	(-12.53)	(-15.05)	(-12.62)	(-11.38)	-(7.54)
$0.5h \leq t< 1h$	-38.10		-2.86***	-2.14***	-1.79***	-1.97***	-1.48***	-1.30***	-0.73***
	(-1.06)		(-7.85)	(-9.77)	(-10.72)	(-9.61)	(-9.55)	(-9.84)	(-5.76)
$1h \leq t < 5h$	-0.03			-2.06***	-1.88***	-1.81***	-1.22***	-1.20***	-0.68***
	(-0.13)			(-17.98)	(-15.54)	(-14.34)	(-15.24)	(-13.12)	(-9.73)
$5h \leq t < 24h$	3.99						-0.74***	-0.83***	-0.40***
	(0.94)						(-11.86)	(-12.65)	(-6.15)

meier and Parker, 2007; Garrett and Sobel, 1999; Gao and Lin, 2012). This chapter investigates the trading behavior of retail investors in a market dedicated to short-term speculation. German investment banks provide retail investors with the opportunity to trade highly leveraged products ideally suited to speculate and/or gamble.

I use a two-fold approach to capture retail investor performance on a trade-by-trade basis. First, I calculate returns for every trade in the sample assuming different holding periods, ranging from 30 minutes up to 5 days. Second, I adapt an algorithm based on backend data of Stuttgart Stock Exchange to match buy and sell orders coming from the same routing provider/broker and, thus, retrieve actual holding periods for the majority of the total sample.

I find that retail investors' performance strongly depends on the underlying type of the investment: Index or stocks. They have a positive return if they speculate on mid term index movements, and a negative return when speculating on single constituents or intraday index movements. However, risk-adjusted returns show that overall investment strategies involving knock-out warrants perform badly on a risk-adjusted basis. Negative performance of retail investors is largely driven by transaction costs. Transaction costs reduce wealth of investors by approximately 6% on average.

Trading intensity of retail investors in products with a stock as underlying increases around news. However, retail investors do not have any informational advantage and no predictive power whatsoever.

Products with extreme returns for 'correct bets' seem to greatly attract speculators and gamblers. It seems that investors are more or less decreasing their wealth to indulge in the adrenaline of trading highly leveraged products.

Chapter 7

Conclusion and Future Research

"[There] are questions that many investors simply may not ask because we are humans, not automatons. Susceptible to behavioural biases, to framing, to anchoring, to poor decision making. Regulators need to have the power and expertise - the remit - to anticipate these influences and react to them."

Martin Wheatley (Chief Executive of the Financial Conduct Authority)

7.1 Contributions

STRUCTURED products have been a huge innovative step in financial markets, allowing retail investors to act in dimensions that have not been possible before. Speculating on falling, rising, or sideways markets with linear or disproportional payoffs on commodities, stocks, or currencies. Retail investors have been given the possibility to trade on almost everything they can imagine.

I studied structured products along several dimensions with a focus on the German market. Particularly, I examined both issuers of structured products and investors trading them, as addressed in the following two research questions:

- Do issuers exploit the ignorance of retail investors?

- Is trading in structured products beneficial for retail investors wealth?

Based on the analyses contained in this thesis, answers to these questions can be given briefly as follows.

Contribution 1: Do issuing investment banks exploit the ignorance of retail investors? Over the last years several studies on structured products across different European markets and the US have addressed facets of this question. Overall, they all find that investment banks, which issue products designed for retail investors, add a significant surplus on theoretical fair prices of their products. First, I verify this phenomena for the German market for several product types. The premium, i.e. the difference between observed quoted prices by issuers and theoretical prices, strongly depends on the specific product type and issuer. Second, I analyze several factors that influence the degree of overpricing by issuers. The work at hand provides evidence that issuers pricing policies are influenced by timing factors, such as, the hour of the day, the remaining life time of the product, the demand of retail investors, and the complexity of the product type. Issuers increase their overpricing towards the end of a trading day, and in times of high uncertainty. In addition, I find that investment banks reduce premiums over the life time of their products to achieve additional benefits on the expense of their customers. An in-depth analysis with respect to the demand of investors on an individual trade level reveals that issuers adjust their quoted prices after executed orders. I observe a positive effect on premiums when shares are bought, and a negative impact when shares are sold. One interpretation for this is that investment banks increase premiums when they expect buy orders to dominate, and decrease premiums when sell orders seem to dominate. Finally, products that are observed to be more complex due to their inherent option structure include higher premiums compared to those, which are easier to understand.

Contribution 2: Is trading in structured products beneficial for retail investors wealth? With the introduction of structured products, issuers provide retail investors with great opportunities to participate in stock, FX, and commodity markets. By means of the liquidity provision of issuers and, thus, the easy way of buying and selling specifically designed products for every market movement, investors may feel like professional traders, having theoretically the possibility to achieve fortunes in a short time. However, data of leveraged trading analyzed in this thesis offers a picture that distorts the illusion of retail investors actually behaving like professionals. Although, retail investors trading activity increases around news, i.e. when new information becomes available, analyzing the performance of their trades leads to the conclusion that, in fact, retail investors do not make profits but rather experience heavy losses on average. Such losses are driven to a large extent by implicit and explicit transaction costs. It remains unclear whether investors trade to meet their need of entertainment and gambling, which might compensate them for their losses, or if they actively pursue an increase of their wealth, which just does not work out in their favor. Nevertheless, analyzing retail investor trades with respect to the assumed risks reveals poor investments on average. Investors expose themselves, i.e. their wealth, to great risks to realize potential profits.

Whether the regulator should step in to protect investors from losing money due to their own misplaced actions and, to a smaller extent, the service charge in form of the premium is not for me to judge. However, the following section provides suggestions which could increase the overall reputation of the market for structured products.

7.2 Regulatory Proposals and Implications

This section presents regulatory suggestions to increase transparency and fairness of the market for structured products.

7.2.1 Obligation to Provide Full Transparency

Currently, regulators are debating whether issuers should disclose hidden fees and fair prices of their own products.[1] Although, such an approach would increase the transparency of the market substantially, it remains a difficult task to formalize rules that would prevent issuers from hiding margins in their products. For example, adjusting the volatility parameter in pricing formulas has a huge direct impact on prices

[1]See `http://www.iosco.org/library/pubdocs/pdf/IOSCOPD410.pdf`. Accessed 06/26/2013.

and, thus, can be used as a lever to control prices without actually adding an explicit fee. There is no rule that defines the explicit calculation of the implied volatility or any other involved parameter, which still leaves room for the incorporation of hidden margins. An enforcement of such an approach is therefore rather difficult.

In my opinion, providing more insight information on costs from an issuer perspective would be helpful and increase transparency, but it does not solve problems that actually matter for most investors. A slightly reduced margin does not compensate for overall bad investments that arise through improper use of products due to underestimation of risks and cognitive biases.

As long as structured products are issued as bearer bonds, it is practically impossible for banks to provide liquidity for products of their competitors. Therefore, no direct price competition arises in structured products. Instead of enforcing fair prices, the following approach tries to increase price efficiency through increased competition.

7.2.2 Standardization

In Section 5.4.5, I provide evidence that, although, the number of tradable products is large, products are not directly comparable to each other. Due to the complexity of the component structure and the non-linear pricing of barrier options, products that do not have the same characteristics are hardly comparable. This leads to obfuscation in the market and allows for higher premiums. However, if the regulator would define a strict issuance grid for each underlying type that only allows for specific combinations market transparency could be increased. Issuers would be forced to issue identical products in order to compete for order flow. Figure 7.1 briefly visualizes a sample issuance grid for warrants with DAX30 as underlying. Investment banks are allowed to issue products on every 50 points of the index starting from 0 up to 15,000 points. Maturity dates for products are fixed on specific dates, for example at the end of each quarter. Issuers are allowed to issue their products continuously, but still with respect to the fixed maturity dates. As a result, issuing endless products, i.e. with no maturity date, would not be possible anymore. The frequent adjustments of product characteristics and the hard to understand methodology behind it makes it nearly

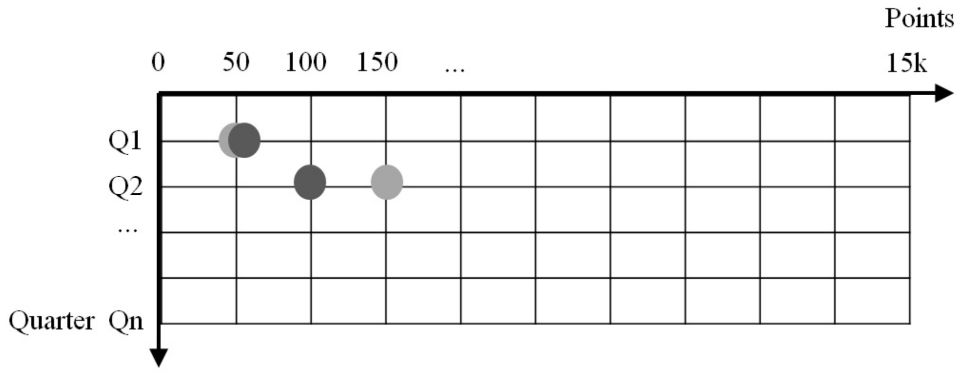

FIGURE 7.1: **Issuance Grid.** This figure sketches an issuance grid for warrants designated on the DAX.

impossible for retail investors to assess a good investment opportunity. As a result, products of different issuers would be more comparable with each other. This could lead to more efficient prices from an investor perspective and, thus, reduce margins without interfering with issuers' pricing models.

However, since the default risk of the issuer is a substantial driving factor for prices of structured products, prices of products with the same characteristics but different issuers might still deviate from each other. Banks with the highest default risk should offer "the cheapest" products from an investor's perspective. Although, all issuers might price their products equally fair, investors could simply focus on the smallest absolute price and order flow is concentrated on the issuer with the highest default risk as a result. Additionally, employing an issuance grid results in a smaller product variety and less possibilities for investors to exactly match their expectations.

7.2.3 Ban of Highly Complex Products

The Financial Services and Markets Authority (FSMA), a Belgian financial regulator, calls distributors of structured products to take part in a moratorium for "particularly complex products"[2]. All signers oblige themselves to not issue products after Au-

[2] A "particularly complex product" is a product that does not meet at least one of the following four criteria: (i) "the underlying value is sufficiently accessible and transparent to the consumer", (ii) "the investment strategy is not overly complex", (iii) "the yield is not calculated on the basis of more than three mechanisms", and (iv) there is "transparency regarding costs, credit risk and market

gust 1, 2011 that fall in the category "particularly complex products". Several other European regulators are discussing product intervention, focusing either on rules for banning products or extended information disclosure. One can reasonably assume that retail investors are not able to understand very complex products in detail, i.e. their pricing mechanisms, but nevertheless they are informed by the issuing bank and resellers of the purpose of the product. Whether this is sufficient to allow investors to trade them remains beyond the scope of this thesis.

7.3 Outlook

While important questions on the German market of structured products have been addressed in this thesis, several aspects remain yet unsolved and, thus, may provide possible avenues for future research. Some of them are briefly discussed in the following.

Hidden margins in exotic structured products

This thesis has addressed several major product types in the German market. However, there is only very limited literature that refers to more exotic product types with highly complex payoff structures. Due to considerable obstacles, such as missing information on internal product characteristics, the calculation of theoretical prices is highly challenging and, thus, provides the ideal environment for a fuzzy pricing of issuers. While many of those products are traded by retail investors, it is still unknown whether investors are being exploited and, if so, to which extent.

Differences in overpricing between regulated markets and over-the-counter markets

Academic literature almost solely refers to the analysis of prices on regulated markets, i.e. on designated trading segments at exchanges. However, OTC markets usually offer a cheaper (in terms of explicit transaction costs) execution throughout the

value". Quotations and a more detailed definition of products that fall under the moratorium can be found here: `http://www.fsma.be/en/in-the-picture/Article/nipic/faqa.aspx#4`. Accessed 07/18/2013.

day. Additionally, trading hours are extended compared to regulated markets. So far there are almost no empirical studies whether prices at OTC markets and regulated markets are different from each other. Since most turnover in German structured products is generated in OTC markets this question is highly relevant for retail investors.[3]

Sensitivity of retail investors to hidden margins

As already pointed out above, current political debates discuss the disclosure of hidden margins incorporated in product prices. Capturing the sensitivity of retail investors towards inherent costs could provide insights for future regulatory initiatives concerning hidden costs. Additionally, it would be of interest to examine whether investors experience any learning effects regarding inherent costs of products. Products offering better prices would attract more order flow compared to worse priced products of competitors. Thus, investors may provide independently a better environment for an enhanced price competition between different issuers.

Technical trading as motivation for trades in leverage products

Pattern recognition and chart tools are becoming increasingly popular among retail investors, being provided on all major financial information portals. Many internet sources offer financial advice based on technical analysis presenting a source of information for retail investors. It is of great interest whether retail investors use technical analysis as one of the main sources of information. Due to the excessive amount of HFT trading in stock markets, trading on technical patterns might be a substantial source of misguided trades. HFT are easily able to use momentum effects to push prices in a desired direction to pick up uninformed small investors.

Investor comprehension and investor decision

Another avenue for future research is the interaction between financial literacy and investment decisions. This could include correct understanding of product risks,

[3]There are no publicly available statistics regarding the actual turnover of OTC markets versus regulated exchanges. However, according to professional traders at Stuttgart Stock Exchange the share of OTC turnover relative to the total turnover ranges approximately between 70%-80% in Germany.

expected returns, and influencing parameters. To which extent are retail investors' choices of investing into structured products influenced by a lack of financial literacy? Are products still attractive if all risks are understood and costs are fully disclosed?

7.4 Summary

In this chapter, I have presented my major contributions to the literature, based on the work at hand. There is significant evidence that issuers systematically abuse their monopolistic power of quoting prices to gain profits on expenses of retail investors. However, whether or not this extents the benefit some investors might see in those products is left to those who have actually traded them. As for my sample and observation period, I can conclude that retail investors, on average, reduce their wealth significantly by speculating with leverage products.

Based on the results in this thesis, I outlined several suggestions for regulators to increase transparency and market efficiency, which includes banning highly complex products and the introduction of a standardized issuance grid for issuers.

Additionally, I have outlined several opportunities for future research to establish a better understanding of the market for structured products. Besides extended analyses on the hidden product premium and its differences between trading venues, a major future focus of research may lie on the interaction of financial literacy and investor decision making.

Appendix A

List of Abbreviations

A.1 List of Abbreviations

BaFIN Bundesanstalt für Finanzdienstleistungsaufsicht (German Financial Supervisory Authority) ... 22
BGB Bürgerliches Gesetzbuch (German Civil Code) ... 22
BörsG Börsengesetz (Stock Exchange Act) ... 23
DAX Deutscher Aktienindex ... 38
DDV Deutscher Derivateverband (German Derivatives Association) ... 13
EOD End-of-Day ... 54
EUREX European Exchange ... 14
EURIBOR Euro Interbank Offered Rate ... 69
EUSIPA European Structured Investment Products Association ... 16
EUWAX European Warrant Exchange ... 11
FCA Financial Conduct Authority ... 3
FESE Federation of European Securities Exchanges ... 10
FSMA Financial Services and Markets Authority ... 141
FX Foreign Exchange Market ... 138
GMM Generalized Method of Moments ... 132
HFT High-Frequency Trading ... 24
IOSCO International Organization of Securities Commissions ... 42
ISIN International Securities Identification Number ... 55
KID Key Information Documents ... 23

KIT	Karlsruhe Institute of Technology	a
NDX	Nordic Derivatives Exchange	29
MiFID	Markets in Financial Instruments Directive	23
NYSE	New York Stock Exchange	43
OCO	One-cancels-the-other order	110
OTC	Over-The-Counter	11
PBS	Practitioners Black-Scholes	60
PNAC	Primary News Access Code	58
PRIP	Packaged Retail Investment Products	23
RIC	Reuters Information Code	54
RNSE	Thomson Reuters NewsScope Sentiment Engine	58
SchVG	Schuldverschreibungsgesetz (Debenture Bond Act)	22
SIRCA	Securities Industry Research Centre of Asia Pacific	54
S&P 500	Standard & Poor's 500	35
SPARQS	Stock Participating Accreting Redemption Quarterly-Pay Securities	38
TAQ	Trade and quote	54
TRDTH	Thomson Reuters DataScope Tick History	53
TRNA	Thomson Reuters News Analytics	58
WKN	Wertpapierkennnummer	55
WpDVerOV	Verordnung zur Konkretisierung der Verhaltensregeln und Organisationsanforderungen für Wertpapierdienstleistungsunternehmen	22
WpHG	Wetpapierhandelsgesetz (Securities Trading Act)	23
WpPG	Wertpapierprospektgesetz (Securities Prospectus Act)	22

Appendix B

German Product Classification

The following table shows the product classification for the German market of structured products according to the German Derivatives Association. The names and descriptions are extracted without changes from DDV.[1] The classification does not capture all product types tradable in Germany. There are many exotic products that do not fit in the classification scheme. However, trading volume in exotic products is negligible.

[1] http://www.deutscherderivateverband.de/MediaLibrary/Document/Derivate-Liga_A3_2013_EN.pdf. Accessed 2013/24/06.

TABLE B.1: German Classification for Structured Products

Name	Description
Investment Products	
Capital Protection Products with Coupon	Capital Protection Products with Coupon are interest-bearing securities with various additional conditions attached. The amount of interest may depend on the performance of the underlying asset. At final maturity the bonds offer 100 percent capital protection
Uncapped Capital Protection Certificates	With Uncapped Capital Protection Certificates, the issuer promises to repay the nominal amount to the investor at maturity. In addition, there is the potential for attractive returns depending on the performance of one or several underlyings
Reverse Convertibles	With reverse convertibles, interest is paid regardless of the performance of the underlying asset. The type and the amount of the repayment at final maturity depend on whether the value of the underlying asset is equal to, or above or below the strike price on the valuation date. If the value of the underlying asset at the valuation date is at least equal to the strike price, the investor receives the nominal value. If the value of the underlying asset is below the strike price, the investor receives either the value of the underlying asset or the underlying assets themselves
Credit Linked Notes	Credit Linked Notes offer a means of investing in a borrower's credit rating. The amount of interest and the capital repayment are dependent on the borrower's credit rating. As long as the borrower does not experience a credit event, the investor will receive interest payments and,when the note matures, the nominal value. If a credit event does occur, however, the note is repaid early. In this case, interest payments cease, and the amount repaid may be significantly below the nominal value
Discount Certificates	Discount Certificates give a discount on the current price of the underlying. This discount provides a cushion against potential falls in the price of the underlying. In return, investors accept a cap on profits from potential price rises, and they do not receive any dividends
Express Certificates	With Express Certificates, movements in the price of the underlying are monitored at specific intervals (e.g. annually) and compared with the initial price. If, at one of the reference dates, the price is higher than the initial price, the investor receives the nominal value of the certificate plus a predefined additional amount before the end of the term. If the price is not higher than the initial price at the reference date, the process is repeated in the next period taking double the additional amount as a basis, and so on. If the price falls, a cushion generally absorbs any price falls up to a predefined value. It is only if the price falls below this predefined value that losses will arise, as they would with a direct investment in the underlying asset
Bonus Certificates	Bonus Certificates pay a bonus amount at final maturity if the underlying does not reach or breach the specified barrier in the relevant monitoring period. The investor does not receive any dividend payments

TABLE B.1: continued

Name	Description
Tracker Certificates	Tracker Certificates offer exposure to the movements in the price of an underlying instrument. This means that with just one certificate, investors can put their money into an asset class, sector or region, optimizing and diversifying their portfolio
Outperformance / Capped Outerperformance Certificates	With Outperformance Certificates, if the price of the underlying asset goes up, investors receive a return equal to a pre-specified multiple of the return on the underlying asset. Capped Outperformance Certificates offer investors the opportunity for leveraged profit from a rise in the price of the underlying above the strike price within a specified range. The profit is limited by a cap. With products of this type, the investor's exposure to potential losses below the strike price is limited to any loss in the underlying. There is no entitlement to a dividend
Leverage Products	
Warrants	Warrants provide leveraged exposure to rising (call) and falling (put) prices in an underlying. The price is influenced not only by movements in the underlying, but also by other factors such as volatility or the (residual) term. If the price of the underlying at maturity is below (call) or above (put) the strike price, investors lose their entire capital
Factor Certificates	Factor Certificates provide leveraged exposure to both rising (long) and falling (short) prices in an underlying asset. They have no fixed term and are based on a strategy index that reflects the percentage daily change in the underlying using a constant factor. The size of the factor determines the amount by which the strategy index leverages the daily price change in the underlying
Knock-Out Warrants	Like Warrants, Knock-Out Warrants also provide leveraged exposure to rising (call) and falling (put) prices in an underlying. Knock-out warrants track the movements of the underlying on a one-to-one basis. This largely eliminates the impact of volatility. If the knock-out barrier is breached, investors generally lose all their invested capital

Appendix C

Sample Data - Thomson Reuters DataScope Tick History

TABLE C.1: Thomson Reuters DataScope Tick History - Intraday Sample

RIC	Date	Time	GMT Offset	Type	Open	High	Low	Last
ADSG.DE	02-MAR-2009	08:02:00.000	1	Intraday 1Min	22.41	22.81	22.41	22.6
ADSG.DE	02-MAR-2009	08:03:00.000	1	Intraday 1Min	22.63	22.67	22.59	22.67
ADSG.DE	02-MAR-2009	08:04:00.000	1	Intraday 1Min	22.65	22.66	22.65	22.66
ADSG.DE	02-MAR-2009	08:05:00.000	1	Intraday 1Min	22.68	22.72	22.67	22.67
ADSG.DE	02-MAR-2009	08:06:00.000	1	Intraday 1Min	22.61	22.61	22.61	22.61
ADSG.DE	02-MAR-2009	08:07:00.000	1	Intraday 1Min	22.6	22.6	22.52	22.52
ADSG.DE	02-MAR-2009	08:08:00.000	1	Intraday 1Min	22.6	22.61	22.54	22.58
ADSG.DE	02-MAR-2009	08:09:00.000	1	Intraday 1Min	22.61	22.61	22.58	22.58
ADSG.DE	02-MAR-2009	08:10:00.000	1	Intraday 1Min	22.58	22.58	22.58	22.58
ADSG.DE	02-MAR-2009	08:11:00.000	1	Intraday 1Min	22.59	22.59	22.56	22.56
ADSG.DE	02-MAR-2009	08:12:00.000	1	Intraday 1Min	22.55	22.56	22.55	22.56
ADSG.DE	02-MAR-2009	08:13:00.000	1	Intraday 1Min	.	.	.	.
ADSG.DE	02-MAR-2009	08:14:00.000	1	Intraday 1Min	22.55	22.55	22.55	22.55
ADSG.DE	02-MAR-2009	08:15:00.000	1	Intraday 1Min	22.58	22.58	22.58	22.58
ADSG.DE	02-MAR-2009	08:16:00.000	1	Intraday 1Min	22.58	22.61	22.58	22.6
ADSG.DE	02-MAR-2009	08:17:00.000	1	Intraday 1Min	22.61	22.62	22.56	22.62
ADSG.DE	02-MAR-2009	08:18:00.000	1	Intraday 1Min	.	.	.	.
ADSG.DE	02-MAR-2009	08:19:00.000	1	Intraday 1Min	.	.	.	.
ADSG.DE	02-MAR-2009	08:20:00.000	1	Intraday 1Min	22.57	22.57	22.57	22.57
ADSG.DE	02-MAR-2009	08:21:00.000	1	Intraday 1Min	22.57	22.62	22.57	22.61
ADSG.DE	02-MAR-2009	08:22:00.000	1	Intraday 1Min	22.59	22.62	22.59	22.62
ADSG.DE	02-MAR-2009	08:23:00.000	1	Intraday 1Min	22.61	22.64	22.61	22.64
ADSG.DE	02-MAR-2009	08:24:00.000	1	Intraday 1Min	22.61	22.61	22.6	22.6
ADSG.DE	02-MAR-2009	08:25:00.000	1	Intraday 1Min	22.62	22.65	22.61	22.61
ADSG.DE	02-MAR-2009	08:26:00.000	1	Intraday 1Min	22.61	22.61	22.6	22.61
ADSG.DE	02-MAR-2009	08:27:00.000	1	Intraday 1Min	22.65	22.7	22.65	22.67
ADSG.DE	02-MAR-2009	08:28:00.000	1	Intraday 1Min	22.65	22.79	22.65	22.78
ADSG.DE	02-MAR-2009	08:29:00.000	1	Intraday 1Min	22.78	22.8	22.75	22.8
ADSG.DE	02-MAR-2009	08:30:00.000	1	Intraday 1Min	22.76	22.8	22.75	22.8

TABLE C.2: Thomson Reuters DataScope Tick History - End-Of-Day Sample

RIC	Date	Time	Type	Qualifiers	Open	High	Low	Last	Volume
ADSG.DE	01-OCT-2009		End Of Day		36.43	36.45	35.48	35.5	794121
ADSG.DE	02-OCT-2009		End Of Day		35.2	35.67	34.67	34.91	1273350
ADSG.DE	03-OCT-2009		End Of Day	No Trades	.	.	.	.	.
ADSG.DE	04-OCT-2009		End Of Day	No Trades	.	.	.	.	.
ADSG.DE	05-OCT-2009		End Of Day		35.01	35.33	34.71	35.04	568638
ADSG.DE	06-OCT-2009		End Of Day		35.61	36.7	35.61	36	1671110
ADSG.DE	07-OCT-2009		End Of Day		35.89	36.39	34.98	35.13	1491331
ADSG.DE	08-OCT-2009		End Of Day		35.2	35.48	34.25	34.5	2792342
ADSG.DE	09-OCT-2009		End Of Day		34.26	35	34.26	34.85	1366481
ADSG.DE	10-OCT-2009		End Of Day	No Trades	.	.	.	.	.
ADSG.DE	11-OCT-2009		End Of Day	No Trades	.	.	.	.	.
ADSG.DE	12-OCT-2009		End Of Day		35.15	35.39	34.7	34.75	1056807
ADSG.DE	13-OCT-2009		End Of Day		34.51	34.88	34.23	34.31	1220124
ADSG.DE	14-OCT-2009		End Of Day		34.71	35.97	34.71	35.76	2103105
ADSG.DE	15-OCT-2009		End Of Day		35.95	36.44	35.78	36.3	1270285
ADSG.DE	16-OCT-2009		End Of Day		36.43	36.69	36.05	36.15	1965823
ADSG.DE	17-OCT-2009		End Of Day	No Trades	.	.	.	.	.
ADSG.DE	18-OCT-2009		End Of Day	No Trades	.	.	.	.	.
ADSG.DE	19-OCT-2009		End Of Day		36.4	36.7	36.29	36.6	949438
ADSG.DE	20-OCT-2009		End Of Day		36.95	36.95	35.7	35.81	1388432
ADSG.DE	21-OCT-2009		End Of Day		35.65	35.78	34.85	35.27	2198390
ADSG.DE	22-OCT-2009		End Of Day		34.95	35.17	34.67	34.97	1007232
ADSG.DE	23-OCT-2009		End Of Day		35.29	35.64	34.54	34.7	892444
ADSG.DE	26-OCT-2009		End Of Day		34.99	35.3	33.68	33.73	1474664
ADSG.DE	27-OCT-2009		End Of Day		33.85	34.06	33.27	33.4	1408850
ADSG.DE	28-OCT-2009		End Of Day		33.25	33.43	32.11	32.15	1880985
ADSG.DE	29-OCT-2009		End Of Day		32.33	33.19	32.25	32.76	1926726
ADSG.DE	30-OCT-2009		End Of Day		32.98	33.73	31.35	31.5	2529549
ADSG.DE	31-OCT-2009		End Of Day	No Trades	.	.	.	.	.
ADSG.DE	01. Nov 09		End Of Day	No Trades	.	.	.	.	.

Appendix D

Sample Data - Stuttgart Stock Exchange Data

Data descriptions are derived from Boerse Stuttgart (2012).

TABLE D.1: Stuttgart Stock Exchange - Master Data Description

Variable	Description
Type	Product type (AZE = Certificates, WAR = Warrants, KO = Knock-out products, EXO= Exotic products, AKA = Bonds) Format: String Length: 3
OptionType	Option type of the security (call/put). Format: String Length: 4
IssuerName	Name of the issuing bank. Format: String Length: 50
WKN	A German identification code (Wertpapierkennnumber). Format: String Length: 6
ISIN	International Securities Identification Number Format: String Length: 12
ExerciseType	Execution type (e=European, a=American) Format: Character Length: 1
Underlying	ISIN of the underlying security. Format: String Length: 12
StrikePrice	Strike price of a derivative. Format: Real Length: 25
Currency	Currency of quoted prices (e.g. EUR = EURO) Format: String Length: 25
ExpirationDate	Expiration day of the security. If endless, value is not set. Format: TT.MM.YYYY Length: 10
SubscriptionRatio	Numeric value which represents the subscription ratio when referring to derivative instruments. Format: Real Length: 10
ProductName	Official name of the financial instrument as given by the issuer. Format: String Length: 50
FirstTradingDay	First trading day of the security on Stuttgart Stock Exchange. Format: TT.MM.YYYY Length: 10
LastTradingDay	Last trading day of the security on Stuttgart Stock Exchange. Format: TT.MM.YYYY Length: 10

TABLE D.1: continued

Variable	Description
Description	Contains the security description. Usually, in German. Format: String Length: 200
Cap	Some securities have a upper or lower threshold for its payoff profile. The threshold value is called Cap. Format: Real Length: 25
SecurityLevel	Denotes the barrier level of a financial product. Format: Real Length: 25
KnockOutBarrier	Denotes the knock-out barrier level of a financial product. Usually, this field is a substitute to *SecurityLevel*. Format: Real Length: 25
InterestRate	Interest rate for regular defined payments. Format: Real Length: 25
Rolling	Indication whether the issuer rolls characteristics such as the knock-out barrier of the financial instrument (j=yes, n=no). Format: Character Length: 1
PercentageQuotation	Provides information whether the product is noted in percent (n=no, j=yes). If so, sizes of order data are multiplied by 100 Format: Character Length: 1
SecurityLevelValidFrom	Starting date of validity of the security level. Format: TT.MM.YYYY Length: 10
BonusLevel	Numeric value for the bonus level of bonus certificates. Format: Real Length: 25
DateOfPayment	Date when issuer resolve the payoff of a financial instrument. Format: TT.MM.YYYY Length: 10

TABLE D.2: Stuttgart Stock Exchange - Order Data Description

Variable	Description
Ordernumber	An integer number which serves as unique identifier for each order sent to Stuttgart Stock Exchange. The order number remains the same as long the order is valid. Format: Integer Length: 12
Timestamp	Date and time of the status change of the order. Format: YYYY-MM-DD hh:mm:ss.sss Length: 23
Code	A integer number which defines the status of the order. Format: Integer (001: submission, 003: modification, 005: cancellation, 011: execution) Length: 3
ISIN	International Securities Identification Number. Allows for identification of the traded product. Format: String Length: 12
Buysell	A character that defines a buy (K) or sell (V) order. Format: Character Length: 1
Size	A real number which represents the submitted number of shares of the order. It is not necessary equal to the number of executed shares. Format: Real Length: 20
Limit	A real number which stands for the limit price of the submitted order. Depending on the trade direction this either results in a minimum or maximum price threshold for the trade execution. Format: Real Length: 20
Tradeprice	A number which identifies the execution price of the order. It is set to *NULL* for orders with status unequal *011*. Format: Real Length: 20
Tradequantity	A number which identifies the number of executed shares. Format: Real Length: 20
RoutingID	A number which identifies the routing provider of the order. Format: Integer Length: 4

TABLE D.3: Stuttgart Stock Exchange - Order Data Sample

Ordernumber	Timestamp	Code	ISIN	WKN	Buysell	Size	Limit	Tradeprice	Tradequantitiy
911023951953	40119.66313	11	DE000CM30GV6	CM30GV	NULL	NULL	NULL	0.61	100000
911024312908	40119.66313	5	DE000DB90V42	DB90V4	NULL	27200	NULL	NULL	NULL
911023951959	40119.66313	1	DE000CM05SV3	CM05SV	V	394	0	NULL	NULL
911023951957	40119.66314	11	DE000CG051E6	CG051E	NULL	NULL	NULL	3.52	1000
911024312871	40119.66314	5	DE000DB54SM1	DB54SM	NULL	20000	NULL	NULL	NULL
911023804932	40119.66315	1	DE000BN7CP40	BN7CP4	V	700	0	NULL	NULL
911029101610	40119.66315	1	DE000CM325Z1	CM325Z	K	500	2.2	NULL	NULL
911024250729	40119.66316	5	DE000DB69DQ2	DB69DQ	NULL	20000	NULL	NULL	NULL
911024052580	40119.66316	1	DE000PAH0038	PAH003	V	100	52.5	NULL	NULL
911023951959	40119.66317	11	DE000CM05SV3	CM05SV	NULL	NULL	NULL	9.76	394
911027301312	40119.66317	11	XS0410299357	ENAG0S	NULL	NULL	NULL	106.83	50000
911023902865	40119.66318	1	NL0000118024	614225	V	1000	0	NULL	NULL
911024205624	40119.66318	5	DE000DB16T05	DB16T0	NULL	3000	NULL	NULL	NULL
911024209585	40119.66318	5	DE000DB8VX39	DB8VX3	NULL	1000	NULL	NULL	NULL
911023804932	40119.66319	11	DE000BN7CP40	BN7CP4	NULL	NULL	NULL	29.98	700
911024209636	4011966319	1	DE0009807016	980701	K	500	42.77	NULL	NULL
911024313010	40119.66323	1	DE000DB5MB21	DB5MB2	V	20000	0.68	NULL	NULL
911024311891	40119.66323	3	DE000A0MFJX5	A0MFJX	NULL	50000	107.4	NULL	NULL
911023753460	40119.66324	3	DE000DB4ZM24	DB4ZM2	NULL	500	3.22	NULL	NULL
911024311926	40119.66324	3	DE000A1AHTR5	A1AHTR	NULL	100000	113.4	NULL	NULL
911024311928	40119.66324	3	DE000A1AHTR5	A1AHTR	NULL	100000	107.8	NULL	NULL
911024209637	40119.66325	1	DE000LBB11G2	LBB11G	K	85	0	NULL	NULL
911024359722	40119.66326	1	DE000AA1V2Q0	AA1V2Q	V	1542	0	NULL	NULL
911024209639	40119.66328	1	DE000BN39TB2	BN39TB	V	1000	2.05	NULL	NULL
911029101611	40119.66328	1	DE000CM2MY91	CM2MY9	V	200	3.45	NULL	NULL
911024359724	40119.66328	1	DE000WLB2S76	WLB2S7	V	60000	0	NULL	NULL
911024101927	40119.66329	1	DE000CM5YHB3	CM5YHB	K	443	5.18	NULL	NULL
911024209641	40119.6633	1	NL0000417111	ABN3HS	V	50	17.17	NULL	NULL
911024209643	40119.6633	1	DE000CM0BVV1	CM0BVV	V	150	11	NULL	NULL
911024209639	40119.66331	3	DE000BN39TB2	BN39TB	NULL	1000	0	NULL	NULL
911024359725	40119.66331	1	DE000A1ALVC5	A1ALVC	K	5000	106.6	NULL	NULL

Appendix E

Sample Data - Thomson Reuters News Data Description

The following data description is extracted directly from Thomson Reuters (2008a) and Thomson Reuters (2008b). I exclude all variable descriptions that are not relevant for my analyses.

TABLE E.1: Thomson Reuters News Data

Variable	Description
timestamp	Timestamp (GMT) of the item. Format: DD MMM YYYY hh:mm:ss.sss Length: 24
stock_ric	Reuters Instrument Code for the stock for which the measures apply. Format: String Length: 14
item_id	Unique identifier for a news message. Format: String Length: 64
relevance	A real valued number indicating the relevance of the news item to the asset. It is calculated by comparing the relative number of occurrences of the asset with the number of occurrences of other organizations and commodities within the text of the item. For stories with multiple assets, the asset with the most mentions will have the highest relevance. An asset with a lower amount of mentions will have a lower relevance score. Format: Real Length: 10
sentiment	This field indicates the predominant sentiment class for this news item with respect to this asset. The indicated class is the one with the highest probability Format: Integer Length: 15
lnkd_ctn[1-5]	The count of linked articles in a particular time period gives a measure of the novelty of the news being reported - the higher the linked count value, the less novel the story is. If the count is zero, then the current item can be considered novel as there are no similar items reporting the story within the history period. Format: Integer Length: 15
pnac	Primary News Access Code; a semi-unique story identifier. Format: String Length: 14

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