Information Disclosure, Competition, and Sustainability in Retail Financial Markets

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Nils Jonathan Krakow
from Germany

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Prof. Dr. Marc Chesney
Prof. Dr. Thorsten Hens

The Faculty of Business, Economics and Informatics of the University of Zurich hereby authorizes the printing of this dissertation, without indicating an opinion of the views expressed in the work.

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Contents

Part I

Introduction and Summary of Research Results

Introduction

Investors face numerous challenges when making investment decisions. Which kind of retail financial product suits their needs best? How to select between several similar products from different financial institutions? When to divest from a product or to invest in a new one? Answering these questions requires the weighting of many different factors with sound information and solid financial knowledge. However, investors—particularly retail investors—are often confronted with limited expertise and bounded capabilities to process new information. Accordingly, it is not surprising that retail investors tend to make investment decisions that, from a normative view, might not be in their best interest, given the complexity and the often confusing financial products offered to them (Campbell, 2006; Calvet, Campbell, and Sodini, 2007; Tufano, 2009). Hence, since sellers of those financial products usually have superior information than their buyers (Carlin, 2009; Carlin and Manso, 2011), retail investors often rely on the provided and presented information.

In this dissertation, entitled "Information Disclosure, Competition, and Sustainability in Retail Financial Markets", I examine different retail financial products. Motivated to understand investment decisions in more detail and contribute to a more sustainable world in general, I investigate the relation between financial products for retail investors, the provided salient information, and the corresponding value of the information for investors. This dissertation addresses questions like what kind of information is salient to investors? Which news about their products do financial institutions provide and highlight? Which information should be taken into account for the investment decision, and is the provided information accurate? In three empirical papers, employing a wide range of different research methods, e.g., laboratory experiments, textual analysis, cluster analysis, I derive several answers to these questions.

The first essay of my dissertation investigates the market for structured products in Switzerland. These products are often fairly complex, and most retail investors have limited experience investing in them (Henderson and Pearson, 2011; Célérier and Vallée, 2017). Choosing one of those products is often associated with a lot of uncertainty, and therefore, the provided and salient information is crucial for investors. In this essay, my co-authors and I investigate both the demand and the supply side of yield enhancement products. We document that these products' inherent complexity, combined with salient information, i.e., the coupon of these products, is a driver of high margins. This fact is further reinforced by a high degree of competition among issuers.

The second and third essay focuses on a different retail financial product as well as another region by analyzing the market for mutual funds in the United States. The U.S. mutual funds market is quite large, complicating investors' decision process for the mutual funds to invest in (Sirri and Tufano, 1998; Hortaçsu and Syverson, 2004). The second essay analyzes the value and accuracy of the information provided in mutual fund prospectuses. Since every mutual fund in the U.S. is mandated to provide key information to (potential) investors, we examine whether the provided qualitative information is accurate and should be considered by investors when making an investment decision.

Finally, the last essay takes a closer look at another specific information piece provided by mutual funds: the mutual fund names. This essay investigates the accuracy of the information embedded in mutual fund names and documents that funds often deviate from the stated style in them.

However, before providing the details of the research papers, I would like to establish the foundations of my work in this chapter. In general, all essays contribute to the field of household finance. Hence, what is household (consumer) finance? According to the two presidential addresses of Campbell (2006), and Tufano (2009), household finance asks how investors make financial decisions and how regulatory interventions affect the provision of financial services. It is the normative and positive study of how institutions can provide financial goods and services to satisfy households' objectives (Guiso and Sodini, 2013).

In a perfect world, investors would, without difficulty, achieve their objectives by making suitable investment decisions as long as they have all relevant information. Simultaneously, competition among financial institutions would ensure the accuracy of the provided information. Since otherwise, the company would be forced out of the market.[1] Thus, based on these assumptions, all decisions would be beneficial for the investors in the long-term, and we would live in a sustainable and stable financial system. Obviously, this is a normative and not a positive description of our world. In reality, it is well documented that households experience notable welfare costs due to investing mistakes (Calvet et al.,

[1]Classic microeconomics predicts price convergence to marginal cost in the presence of high competition.

2007). While investors have to make a wide array of financial decisions, many retail investors have only limited ability to make decisions that are always in their best interest. Hence, what are the constraints keeping retail investors from achieving their objectives by deviating from the prescriptions of normative finance?

On the one hand, it might be their behavior and the corresponding biases that investors exhibit. This view is covered in the behavioral finance literature. Especially, the first essay of this dissertation contributes to this literature. This research field focuses on investors' behavior and provides some answers to potential behavioral constraints (biases). It primarily deals with the psychology and sociology of investors as well as the mechanisms that influence individuals' financial decisions.[2] On the other hand, we can examine the setting in more detail in which retail investors have to make financial decisions. Contributing mainly to this view, I investigate in this dissertation in particular what kind of information is provided, which information is salient, and how investors react to it.

To elaborate more on potential constraints, let's think about a world of full shared information between financial institutions and investors. In this world, as soon as "rational" investors have all information at hand, they are able to make decisions that are always in their long-term interest. Since rational investors exhibit no biases, they decide based on the information available to them and accordingly manage to meet their preferences. Regulators only have to ensure that disclosures are complete and that the content provided to (retail) investors is accurate. Indeed, several government policies attempt to improve decision-making by setting disclosure requirements so that retail investors can make informed decisions. Hence, information disclosure is an essential component of regulation in financial markets (Goldstein and Yang, 2017) and improves market quality in an economy with exogenous information. While disclosure rules are certainly one way to influence retail investors' decisions, they have the advantage of not restricting the investment decision space. Thus, from a regulatory perspective, disclosure plays a significant role in protecting investors without being prohibitive.[3]

However, we also know that even in theory, full shared information does not converge to an equilibrium (Grossman and Stiglitz, 1980). In reality, there are at least two limitations that restrict convergence towards such an equilibrium. First, there are limitations in

[2] See, for instance, Shleifer (2000) for an introduction to behavioral finance, and Kahneman (2003) for an overview on bounded rationality.

[3] Note, that I focus on ex-ante disclosures. I do not analyze strategic ex-post disclosures, which depend on the received signal of the party and is part of the asymmetric information literature (see, e.g., Akerlof, 1970; Grossman, 1981; Milgrom, 1981; Dye, 1985; Acharya, DeMarzo, and Kremer, 2011).

retail investors' search and analysis of information. As outlined above, retail investors exhibit bounded rationality. Second, theoretical and empirical literature discusses the exploitation of information asymmetries between financial institutions and retail investors (Bolton, Freixas, and Shapiro, 2007; Bergstresser, Chalmers, and Tufano, 2008; Carlin, 2009; Stoughton, Wu, and Zechner, 2011; Carlin and Manso, 2011; Mullainathan, Noeth, and Schoar, 2012; Zingales, 2015; Egan, 2019). Due to the informational advantages for the sell-side (Carlin, 2009; Carlin and Manso, 2011), and depending on the market structure, this results in potential conflicts of interest between financial institutions and retail investors.

Hence questions about the relation of the shared information between the supply and the demand side often relate to industry competitiveness. The role of competition in this context, however, is complex. On the one hand, competition among financial institutes can be a mechanism to increase credible information disclosures (Bolton et al., 2007). Hence, market forces might be a way to protect investors and to decrease this conflict of interest. The standard economic theory claims that all information is directly consolidated into market prices in competitive markets, and suppliers of financial products have to pass on all profits to their customers. However, this relation only holds if there are no frictions in the markets. Rent-seeking activities, which are common in finance (Shiller, 2003), are a clear indication that markets are not fully efficient.[4]

On the other hand, competition might even amplify this conflict of interest. For instance, an increase in competition leads to more pressure among the financial advisors (Mehran and Stulz, 2007). Accordingly, financial institutions might be attempted to shroud specific product attributes by increasing the obfuscation and complexity of financial products (Gabaix and Laibson, 2006; Carlin, 2009) or even to disclose misleading information (Reurink, 2018). In this case, the provided information might not facilitate investors' decisions making. In other words, potential incentive conflicts exist in the provision of almost all financial products, resulting in various types of externalities and potential information failure.

Hence, authorities and the regulation of retail financial products play an essential role (Campbell, Jackson, Madrian, and Tufano, 2011). Regulatory frameworks aim to protect households from making mistakes and being exploited by financial intermediaries aware of their limitations. In particular, in the second and third essay, my co-authors and I elaborate on the importance of the regulatory authorities, namely the U.S. Securities

[4]For a survey of the costs that investors bear searching for positive performance, see also French (2008).

and Exchange Commission (SEC). Its mission is to ensure the quality of the information provided by financial institutions and companies to their investors.

Finally, the papers in this dissertation are also related to sustainability. While in our days, the term sustainability in the context of finance is closely linked to the environmental and social performance of a financial asset, sustainability encompasses many more aspects related to the durability and stability of the financial system. Indeed, it is challenging to agree on a unique definition of the term sustainability, particularly in the context of finance. However, how can an investment decision be sustainable if it is not in the long-term interest of the investors? Therefore, I refer to a very comprehensive definition of the term sustainability. The Cambridge Dictionary (2020) defines sustainability as "the quality of causing little or no damage [...] and therefore able to continue for a long time." Accordingly, finance can only serve society if the investment decisions are in the investors' long-term interest. Accurate and valuable information is a prerequisite to obtaining a sustainable equilibrium. Hence, I relate in this thesis sustainability to welfare-maximizing behavior. Friedman (1970) argues that firms profit-maximizing behavior and the private donation of the firm owners would directly maximize welfare, and we should not expect costly pro-social behavior from financial institutes, firms, and their investors. However, the more recent literature emphasizes that a pro-social behavior can be the welfare-maximizing behavior if investors experience frictions or if firms can use it as a comparative advantage (see, e.g., Bénabou and Tirole, 2010; Magill, Quinzii, and Rochet, 2015; Hart and Zingales, 2017). Thus, there are still unanswered research questions that demand to evaluate financial institutions' current practices and whether these are in the interest of investors and society in general. Accordingly, the details of my essays are the following.

In the first essay, *Low Interest Rates, Bounded Rationality, and Product Complexity: Demand and Supply Effects for Retail Financial Markets*, we study the market for yield enhancement products in Switzerland. It is written together with Marc Chesney and Felix Fattinger. In this essay, we investigate the post-global Financial crisis market for retail structured products. Our study focuses on a prototypical and particularly interesting retail financial market: the market for so-called yield enhancement products (YEPs). Generally, the difficulty in studying the role of specific bounds to rationality in the context of financial innovation lies in the isolation of behavioral channels within the endogenous determination of competitive equilibrium outcomes. To overcome this potential endogeneity problem, we combine the power of laboratory control with the external validity of representative field data.

In the first part of the essay, we experimentally study the demand for "complex products" controlling for different investment environments. First, we find that product margins go hand in hand with participants' misestimation of Multis' inherent correlation risk, which directly translates into higher margins relative to Singles. Second, our results indicate a negative relation between interest rate levels and participants' willingness to bear the risk. In line with Lian, Ma, and Wang (2019), we provide evidence for an increased appetite for risk in an environment of low-interest rates. Lower interest rates significantly increase the demand for both Singles and Multis, while we do not observe any impact on participants' relative willingness-to-pay (WTP). Third, we find participants' WTP to be decreasing in their relative risk aversion but increasing in their level of overconfidence.

The second main contribution of the essay is the provision of evidence for the external validity of the experimental findings by analyzing a unique data set spanning 4,460 Barrier Reverse Convertibles (BRC) on U.S. equities issued in Switzerland between 2008 and 2017. For each BRC, we estimate expected issuer margins implied by standard pricing techniques and calculate realized issuer returns based on actual cash flows at maturity. We find banks' average issuance margin to be consistently higher for Multis (at least 4.0%, depending on correlation estimations) relative to Singles (2.0%). Thus, the misestimation of correlation effects documented in our experiment provides a precise mechanism that can explain the margin differences observed in the field.

Looking closer at the issuer of those products, we then document that the number of different issuers remains high throughout. Based on this fact, we conclude that there is considerable competition among BRC issuers for retail investors. Therefore, the third key insight from this essay is the positive relationship between competition and an increase in complexity. More precisely, we document that by increasing the issued products' complexity, financial institutions can partly shield their margins from competition pressure.

Mutual Fund and Qualitative Disclosure is the second essay in this dissertation, written jointly with Timo Schäfer. This essay studies the informational value of U.S. mutual funds' qualitative disclosures. In the United States (as well as in Europe), mutual funds are mandated not only to inform about yearly measures on performance but also to provide up-to-date qualitative information on their investment strategies, investment objectives, and principal risks (SEC, 2009). Accordingly, we ask a straightforward question: What is the informational value of these qualitative disclosures or to put it into an investors' perspective: How carefully should investors read the text in a prospectus of a mutual fund?

In this essay, we show evidence that the provided information is indeed valuable. For this, we analyze the summary sections of active U.S. open-end equity funds between 2011 and 2018. This is—to the best of our knowledge—the first study that analyzes in detail the qualitative disclosure in fund prospectuses. The detailed contributions of this essay can be summarized as follows. First, we document a positive relation between the amount of text on disclosed risk and the actual risk a fund is exposed to. The riskier a fund invests, the more a fund writes about it in its risk statement. This finding is confirmed for the general risk, the systematic risk, and the idiosyncratic risk of a fund. However, we find that this positive relation only holds if we control for characteristics at the investment company level. Accordingly, we argue that for measuring the informativeness of the disclosures, we have to take into account the variation attributable to investment company fixed effects.

In the second part of the essay, we then introduce two more advanced textual measures to examine in more detail the actual written content of funds disclosures. For this, we use our laboratory setting in a more fine-tuned analysis to determine how similar the textual content of funds' disclosures is. Again we confirm that a substantial part is determined at the investment company level. Nevertheless, around one-third of the variation in the content of funds' risk disclosures is fund-specific. To investigate the textual information in funds' summary sections in more detail, we therefore decompose the content into an informative part and into a standard part (see also Hanley and Hoberg, 2010). This allows us to analyze the implications of fund-specific informativeness regarding funds' risk-taking behavior, funds' performance, and funds' flows. Our results indicate that (i) funds with a higher risk exposure inform more accurately about their risks, (ii) the more informative the qualitative disclosure of a fund, the higher the fund's contemporaneous alphas (see also (Kostovetsky and Warner, 2020)), and (iii) funds with more informative disclosures attract higher fund flows. Moreover, in line with Li (2010); Cohen, Malloy, and Nguyen (2020), we show that regular content-based updates of the relevant information predict future fund performance. Overall, this essay provides evidence for informative qualitative disclosures of fund prospectuses while still highlighting the considerable heterogeneity across funds, mainly attributed to investment company characteristics.

The third essay, *Mutual Fund Names and Style (Mis-)Information*, analyzes the accuracy of mutual fund names. This essay is joint work with Anne-Florence Allard and Kristien Smedts. Like the second essay, the research question focuses on the U.S. mutual fund industry; however, in this essay, we examine the information provided to investors in the mutual fund names.

As already outlined at the beginning of this chapter, investors often look for simplified information for their investment decision. Therefore, salient information is often crucial. In the mutual fund industry, it is common practice that mutual funds inform via their name about the investment style that they pursue. Hence, recognizing the importance and potential influence of such names in investors' investment decisions (SEC, 2001), the SEC introduced in 2001 Rule 35d-1. This rule regulates mutual fund names, requiring, for instance, that at least 80% of a mutual fund's portfolio is invested in the asset class mentioned in the name, e.g., equity. However, this rule leaves two loopholes. First, there is no strict regulation of the use of terms referring to the size factor, e.g., small or large-cap. Second, terms indicating an investment strategy, such as growth or value, are not regulated. Focusing on these loopholes, we document that a significant proportion of mutual fund names provides inaccurate information. More precisely, the funds' investment styles do often not align with the given names.

Hence, complementary to the two studies of Cooper, Gulen, and Rau (2005) and Espenlaub, ul Haq, and Khurshed (2017) who both study the motivation for and consequences of fund name changes, we also investigate the cases where funds keep their names but change their investment strategies. First, to classify the fund investment strategies, we estimate for all active U.S. equity funds that refer in their names to an investment strategy the four-factor model of Carhart (1997). Next, we take the factor loadings and sort funds into investment style clusters according to their similarity. Based on this classification, we then assign an accuracy measure to each fund. We find that fund name inaccuracy is a widespread phenomenon. A large proportion of mutual funds has an inaccurate name at least once in their lifetime – mostly triggered by strategy changes and less by fund name changes. Regarding the motivation of fund managers to deviate from the investment styles stated in a fund name, this essay also highlights the role of competition, i.e., pointing to the tournament hypothesis (Brown, Harlow, and Starks, 1996; Chevalier and Ellison, 1997). The fund industry can be seen as a tournament in which funds in the same investment category compete for assets under management. Since the managers' compensation is often linked to the size of assets under management, managers have an incentive to be ranked among the top-performing funds by the end of the year. Consequently, when their performance over the course of the year is not good, they might be willing to deviate from the investment style stated in their names. In line with the predictions of prospect theory (Kahneman and Tversky, 1979), managers of mutual funds are willing to take more risk when they are in the (relative) loss area. The results of the analysis carried out in the third essay provide evidence supporting this tournament hypothesis. Finally, investigating the consequence of the deviating behavior of the fund, we document that investors experience difficulties in responding—expressed by abnormal fund flows—to the misleading information in mutual fund names while, at the same time, they do not benefit, on average, from such deviations.

In summary, this dissertation sheds light on the relation between product information for some financial products and the corresponding value of this information for retail investors. The results and the underlying methods in this dissertation are useful to answer a wide range of economic questions. In all three essays, I find evidence that the provided financial information, particularly salient information, and the obligatory disclosure rules mandated by the authorities can significantly affect the interest of retail investors. Specifically, competition and the motivation to shield profits are essential drivers of financial institutions' actions. Accordingly, only when there is a setting that guarantees the provision of valuable and accurate information, investors have the opportunity to take investment decisions that are in the long-term in their best interest. Valuable and precise information disclosure is a precondition for financial stability and the sustainability of financial markets.

The remainder of this dissertation is organized as follows. Part II comprises the research papers. Part III provides the bibliography of the dissertation, and Part IV shows my curriculum vitae.

Part II

Research Papers

Low Interest Rates, Bounded Rationality, and Product Complexity: Demand and Supply Effects for Retail Financial Markets

Joint with Marc Chesney and Felix Fattinger*

This paper studies the market for yield enhancement products (YEPs). We document a substantial increase in volumes, followed by a striking rise in product complexity. This pattern is paralleled by sharply falling and plateauing interest rates. We experimentally show that, while decreasing interest rates increase individuals' willingness to bear risk, it is their risk misestimation that creates demand for more complex products. By analyzing 4,460 issued YEPs, we find that (i) issuer margins are increasing in product complexity, (ii) average investment returns are negative, (iii) product complexity is driven by supply competition while catering to investors' bias in perceiving dependencies.

*Marc Chesney, Department of Banking and Finance, Center of Competence for Sustainable Finance, University of Zurich, Plattenstrasse 32, 8032 Zurich, Switzerland. Email: marc.chesney@bf.uzh.ch; Felix Fattinger, Institute for Finance, Banking and Insurance, WU Vienna University of Economics and Business, Welthandelsplatz 1, 1020 Vienna, Austria. Email: felix.fattinger@wu.ac.at; and Jonathan Krakow, Department of Banking and Finance, Center of Competence for Sustainable Finance, University of Zurich, Plattenstrasse 32, 8032 Zurich, Switzerland. Email: jonathan.krakow@bf.uzh.ch. We are grateful for comments from Francesco d'Acunto, Björn Bartling, Peter Bossaerts, John Cochrane, Marc Egan, Michael Hasler, Thorsten Hens, Spencer Martin, Steven Ongena, Per Östberg, Johan Walden, Alexander Wagner, Michael Weber, Daxeng Xiu, Alexander Ziegler, and seminar participants at the University of Zurich, University of Melbourne, Vienna Graduate School of Finance, the 2018 Research in Behavioral Finance Conference (Amsterdam), and the 2020 North American Experimental Finance Conference (Salt Lake City). Jonathan Krakow acknowledges financial support from the Forschungskredit of the University of Zurich grant no. [FK-17-015].

2.1 Introduction

During the unprecedented period of low interest rates following the Great Recession, the search for low risk investments with positive yields has become increasingly difficult. This new environment has been linked to important demand and supply effects in retail financial markets. On the one hand, recent evidence suggests that low risk-free rates induce yield-seeking behavior among retail investors (Lian et al., 2019). On the other hand, decreasing interest rates have been paralleled by an increase in the supply of structured investment products catered to households (Célérier and Vallée, 2017). Importantly, how exactly interest rates affect the empirically observed product characteristics remains unclear.

Contrary to most financial markets, the market for retail investment products is commonly characterized by a distinct attribution of potential bounded rationality (Kahneman, 2003) among buy-side investors (Gennaioli, Shleifer, and Vishny, 2012) and informational advantages for sell-side investors (Carlin, 2009; Carlin and Manso, 2011; Egan, 2019). Consequently, the literature has emphasized the importance of regulatory policies for distributional outcomes (see, e.g., Tufano, 2009, and Campbell et al., 2011). To assist ongoing regulation, a better understanding of both demand and supply driven mechanisms is crucial for shedding light on the impact of unconventional monetary policies on households' investment decisions and, ultimately, on allocative efficiency and financial stability (Shiller, 2009; Gennaioli et al., 2012).

In this paper, we investigate the post-Great Recession market for retail structured products. We first show that low interest rates increase investors' overall risk tolerance when reaching for predefined yield in return for down-side exposure. Second, our findings suggest that the subsequent rise in product complexity is driven by a sell-side response to investors' risk misestimation, which manifests itself in higher margins for more complex products. Third, while fueled by low interest rates, this increase in complexity appears to mainly result from competition among product issuers. Finally, building on recent insights from cognitive neuroscience, we provide evidence that suppliers' structuring of popular investment products caters to a distinctive bias in humans' perception of dependencies among financial assets.

Our study focuses on a prototypical and particularly interesting retail financial market: the market for so-called yield enhancement products (YEPs) in Switzerland. Foremost, YEPs represent a class of structured products that has enjoyed increasing popularity among retail investors. Combining a fixed rate bond with a short option position, YEPs promise high coupons (Bordalo, Gennaioli, and Shleifer, 2016), while often exposing investors to the risk of unlimited losses. Effectively, the short (put) option converts the product principal into a predefined amount of the underlying asset whenever its price falls below a certain threshold (see Section 2.2.1 for a detailed example). In Switzerland alone, bank deposits contained YEPs worth more than CHF 71bn in 2019, corresponding to approximately 15% of Swiss equity funds' assets under management.[5] Across EU households, YEPs amounted to EUR 500bn in 2017.[6] Strikingly, the rising popularity of YEPs is not solely a European phenomenon. In the US, YEPs are the largest and fastest growing class of retail structured notes with more than USD 100bn sold since 2008 (Vokata, forthcoming).

Furthermore, the Swiss market for YEPs exhibits two features of particular relevance for our study. (i) Originating in the 1990s, it is a mature and – as we will show – highly competitive market. (ii) Due to the central bank's devaluation measures for the Swiss Frank relative to the Euro, investors in Switzerland have faced a decade of remarkably low interest rates (see Figure 2.1).

The emergence of a sharply diverging issuance pattern among the most popular YEPs, so-called barrier reverse convertibles (BRCs), constitutes the starting point of our analysis.[7] While the overall increase in issued BRCs appears associated with decreasing interest rates, there is a subsequent tendency towards the issuance of BRCs with multiple ("Multis") instead of BRCs with only one underlying asset ("Singles") – see Figure 2.1. A very similar pattern obtains from issuance volumes (see Figure 2.9 in the Appendix).

In line with the literature, Multis' larger number of contingencies makes them considerably more complex relative to Singles (Célérier and Vallée, 2017), without offering any liquidity or tax advantages. Moreover, contrary to standard intuition about diversification benefits, BRCs' inherent worst-of payoff structure implies that the risk borne by

[5]See market data provided by Swiss Fund Data available via https://www.swissfunddata.ch/sfdpub/investment-funds.

[6]See the European Structured Investment Products Association (EUSIPA) market reports available via https://eusipa.org/category/market-reports/ and the European Securities and Markets Authority (ESMA) report on "Trends, Risks and Vulnerabilities," No. 2, 2018, available via https://www.esma.europa.eu/press-news/esma-news, respectively.

[7]Reverse convertibles are commonly considered synonymous with structured products (Egan, 2019). Already in 2011, the SEC referred to reverse convertibles as "perhaps the riskiest [structured product] available to retail investors" (see p. 4 of the SEC report "Staff Summary Report on Issues Identified in Examinations of Certain Structured Securities Products Sold to Retail Investors," July 27, 2011, available via https://www.sec.gov/news/studies/2011/ssp-study.pdf). In contrast to standard reverse convertibles, the term "barrier" refers to the barrier characteristic of the embedded put option (see Section 2.2.1 for details).

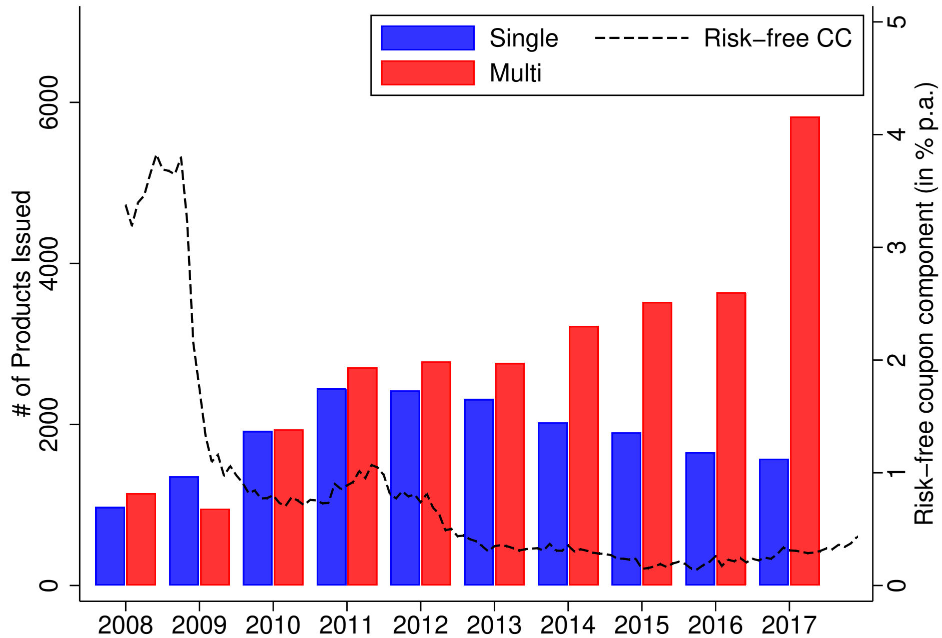


Figure 2.1: **BRCs issuance and interest rates over time**

Figure 2.1 illustrates the evolution of all BRCs issued in Switzerland between January 2008 and December 2017 (left y-axis) and the corresponding development of the average monthly risk-free coupon component ("risk-free CC," right y-axis). For taxation purposes, the coupon (headline rate) of each product is split into an interest component and a premium component, only the former is subject to income tax. We classify BRCs as "Singles" (one underlying asset) or "Multis" (more than one underlying asset), respectively. In total, 47,080 BRCs were issued: 18,583 Singles and 28,497 Multis.

investors is an *increasing* function in the number of underlying assets. Considering that humans often exhibit difficulties in correctly adjusting for correlation effects (see, e.g., Enke and Zimmermann, 2019), the application of a worst-of payoff structure to multiple underlyings is of particular interest here.

What drives this increase in complexity? Are there distinct demand and supply effects? What role does the prevailing interest rate play, and does there exist any evidence of bounded rationality on the part of retail investors? The difficulty in studying the role of specific bounds to rationality for financial innovation lies in the isolation of behavioral channels within the endogenous determination of equilibrium outcomes. We address this challenge by combining the power of laboratory control with the external validity of representative field data. While our experimental approach allows for counterfactual analysis under measurable beliefs, contrasting experimentally identified mechanisms with real-world data is crucial for quantifying their economic implications.

Specifically, to answer the above questions, we proceed in three steps. Aiming for a clean micro-foundation of potential demand effects, we first conduct a laboratory experiment to quantify participants' relative willingness-to-pay (WTP) for BRCs of varying complexity (number of underlying assets). Importantly, the means of laboratory control enable us to study the effects of specific changes to the investment environment in isolation. In particular, we focus on changes in the interest rate of the risk-free investment alternative, as well as the volatility of the underlying asset(s) as the main risk drivers.

Our experimental findings are threefold. First, we find that product margins go hand in hand with participants' misestimation of Multis' inherent correlation risk, which directly translates into higher markups relative to Singles (3.5 percentage points on average). This effect is amplified in an environment of high volatility. Second, our results indicate a negative relation between interest rate levels and participants' willingness to bear risk. Lower interest rates significantly increase the demand for *both* Singles and Multis, while we do not observe a significant impact on participants' relative WTP. Third, we find participants' WTP to be decreasing in their relative risk aversion but increasing in their level of overconfidence. Besides a clear bias in estimating Multis' embedded correlation risk, our experiment demonstrates that, while low interest rates amplify participants' reach for yield, they do not increase the relative popularity of Multis over Singles. This is intuitive, as Singles' headline rates are generally well above historical interest rates. Their relatively lower coupons, compared to Multis, still offer a sufficient substitute for risk-averse, yield-seeking investors (Lian et al., 2019).

In a second step, guided by our experimental evidence, we analyze a data set spanning 4,460 BRCs on US equities issued in Switzerland between 2008 and 2017. For all BRCs, we estimate *expected* issuer margins implied by standard pricing techniques and calculate *realized* issuer returns based on actual cash flows at maturity. We find banks' average issuance margin to be consistently higher for Multis (4.0% and higher, depending on correlation estimates) relative to Singles (2.0%). When controlling for issuer and time fixed effects, issuer margins for Multis are, on average, 2.9 percentage points (pp.) higher than for Singles. Accordingly, for investors, the average realized *return* from investing in Multis is indeed negative (-1.6% p.a. over the risk-free rate). The differences in estimated (2.9 pp.) vs. realized margins (2.6 pp.) are strikingly similar.[8] Overall, these magnitudes

[8]Note, the deviations in levels stem from our conservative discount rate, i.e., the risk-free rate. Given

corroborate our experimental results. The misestimation of correlation risk documented in our experiment provides a clean mechanism that can explain the margin differences observed in the field.

In a final step, we study the dynamics of retail markets in response to low interest rates in more detail. In line with our experimental findings, the outstanding volume of YEPs, including both Singles and Multis, essentially doubled from CHF 36.9bn in 2009 to CHF 73.6bn in early 2019. At the same time, the volume invested in other types of structured products fell sharply until 2011 and stayed fairly stable thereafter. Looking closer at our sample of BRCs, we find the number of different issuers to remain high throughout (average of 23.4), allowing for a substantial time variations in revenue shares. In combination with an average Herfindahl index of 0.14, we conjecture that there is considerable competition among BRC issuers for retail investors. This market perspective is supported by a negative time trend in issuer margins, which is more significant for the easier to compare Singles than for the more complex Multis. Motivated by the introduction of a fast-growing issuer platform in 2014, we provide evidence of aggressive price competition at the product level.

In light of the involved competitive forces, it is natural to further investigate how retail financial markets respond to such an influx of retail capital. Consistent with shielding rents borne by incompletely informed investors (Carlin, 2009), the issuance ratio of Multis to Singles steadily increases over our sample period. However, a closer investigation reveals that this rise in product complexity follows a distinct pattern: instead of proportionally expanding the universe of underlying assets, issuers appear to cater to investors' time-variant preferences for certain blue chip or potential growth stocks, often from the consumer goods sector. According to the Standard Industrial Classification, 44.8% of all underlyings belong to the "Manufacturing" and 23.7% to the "Services" division.

Consistent with evidence from cognitive neuroscience (d'Acremont and Bossaerts, 2016), Ungeheuer and Weber (2020) document that both laboratory participants and stock market investors require compensation for the *frequency* of price comovement rather than actual price correlation, and are thereby effectively neglecting potential tail risk. In line with Ungeheuer and Weber (2020), we find that popular underlying combinations of Multis exhibit a relatively higher frequency of price comovement than price correla-

the objective of our study, and to remain as close as possible to our experimental setup, we do not focus on *risk-adjusted* BRC returns. However, our estimates of issuer margins and realized returns square reasonably well with carefully estimated beta-adjusted returns of YEPs (Singles) issued in the US (Vokata, forthcoming).

tion. Due to BRCs' worst-of payoff structure, a lower correlation among underlying assets actually *increases* the corresponding investment risk.[9] Correlation overestimation, thus, makes such Multis appear less risky to investors. Indeed, we show that the higher the relative discrepancy between comovement frequency and correlation, the higher the estimated product margin in the cross section. Hence, our findings suggest that the increase in complexity appears – at least partially – driven by issuers who cater to retail investors' bias in perceiving dependencies among financial assets.

2.1.1 Literature contribution

Our paper builds on several strands of literature. First, we add to the literature on price and quality dispersion introduced by financial innovation. Traditionally, financial innovation has been considered to arise in response to and for the benefit of previously unmet investor needs (Allen and Gale, 1994; Duffie and Rahi, 1995). However, there is an ongoing debate (Zingales, 2015) and accumulating evidence (see, e.g., Célérier and Vallée, 2017) about financial institutions' strategic exploitation of information asymmetries when catering financial services to retail investors.[10] For instance, Ellison (2005) and Gabaix and Laibson (2006) show theoretically how financial institutions may issue complex products to shroud specific product attributes, which increases search costs and protects rents. Carlin (2009) and Carlin and Manso (2011) illustrate how the rents to issuers of complex products decline with investor sophistication.

Second, our paper relates to the literature on the (mis)pricing of structured products. Henderson and Pearson (2011) analyze the pricing and historical performance of 64 popular retail structured equity products and find that investors receive negative abnormal returns of at least 8% per year relative to dynamically adjusted portfolios with comparable risk. Margins of similar magnitude are found in two large studies of the US market (Egan, 2019; Vokata, forthcoming). For the European market, margins of issuers are slightly lower but still substantial (Wallmeier and Diethelm, 2009; Célérier and Vallée, 2017; Ammann, Arnold, and Straumann, 2018). Moreover, Célérier and Vallée (2017) show that sellers' margins are positively associated with product complexity. Similar to our study, they define an increase in complexity as an increase in payoff scenarios. Hens

[9]The intuition is straight-forward, the lower the correlation, the higher the chance that at least *one* underlying asset performs poorly.

[10]See, e.g., Zingales' presidential address for a reflection on the distribution of benefits from current trends in finance (Zingales, 2015). Chesney, Krakow, Maranghino-Singer, and Münstermann (2018) and Chesney (2018) provide a critical discussion about the general role of finance for society as a whole.

and Rieger (2014) theoretically demonstrate that the popularity of structured products cannot be rationalized by expected utility theory. Egan (2019) and Henderson, Pearson, and Wang (2020) respectively show how brokers use their informational advantage and institutional power to distort households' investment decisions or to manipulate market prices. Ghent, Torous, and Valkanov (2019) document an uncompensated increase in complex risk for mortgage-backed securities.

Third, we contribute to the literature that studies behavioral effects in (retail) financial markets. Bordalo, Gennaioli, and Shleifer (2012, 2013) and Bordalo et al. (2016) show how salience-driven probability weighting and product attribute attention can explain both seminal stock market puzzles and retail investors' reaching for yield under low interest rates. Li, Subrahmanyam, and Yang (2018) illustrate that behavioral proclivity for skewness increases the demand for retail investment products. However, unlike the contracts analyzed by Li et al. (2018), the higher ex-ante likelihood of BRCs' positive payoff scenarios does not appeal to prospect theory preferences. Interestingly, Calvet, Célérier, Sodini, and Vallée (2019) document how narrow framing (Barberis, Huang, and Thaler, 2006) can create space for financial innovation to alleviate retail investors' reluctance to bear financial risk.

Fourth, this paper relates to the experimental literature on complex financial assets. For instance, Rieger (2012) and Kunz, Messner, and Wallmeier (2017) find that probability misestimation increases the subjective attractiveness of complex products. However, both studies do not investigate how such misperception translates into an incentivized willingness-to-pay measure of potentially risk-averse investors and how this is affected by varying interest rates. Carlin, Kogan, and Lowery (2013) show that, in a bilateral trading environment, higher complexity results in increased volatility, lower liquidity, and less trade efficiency.

Finally, our focus on the role of low interest rates on households' investment decisions in the context of retail structured products most directly relates to the important work by Célérier and Vallée (2017). While their sample period accounts for the beginning of the post-crisis decrease in interest rates, our field data fully captures the subsequent prolonged period of (sub)zero risk-free rates. In line with the non-linearity of low interest rates' yield-seeking effect documented in Lian et al. (2019), our experimental results indicate that the complexity increase observed in the field is largely driven by competition rather than interest rate levels per se.[11] Note, while Lian et al. (2019) analyze investment

[11]The already high coupon (headline) rates of Singles are more than sufficient to cover the domain of

decisions for a basic risky asset, the nature of structured products requires verification of their result for more complex assets such as BRCs, which, besides pinning down the mechanism behind mispricing, is the aim of our experiment.

The remainder of the paper is structured as follows. Section 2.2 provides an overview and stylized facts of the Swiss market for retail structured products in general, and for YEPs (BRCs) in particular. Section 2.3 introduces the design of the laboratory experiment and discusses its findings. Section 2.4 describes our product data set in detail and motivates the procedure of our empirical analysis. Section 2.5 presents our empirical results. Finally, Section 2.6 concludes.

2.2 Market for Yield Enhancement Products

As their name suggests, structured products are tailored combinations of different financial securities offering payoff profiles that are otherwise difficult (or costly) to attain for retail investors. Their payoff generally depends on the performance of one or multiple underlying assets, most commonly equities, but also fixed-income instruments or commodities. This payoff dependency is achieved via an embedded derivative component, such as options. Issuers – typically banks – offer structured products to potential buyers on a primary market. Post issuance, these products can be traded on a secondary market, which, however, exhibits relatively low liquidity (see, e.g., Ammann et al., 2018) due to the buy-and-hold strategy of most investors. Given our interest in the structuring and issuance process, our focus lies on the primary market.

In Switzerland, the typical notional (denomination), i.e., minimum investment amount, ranges from CHF 1,000 to CHF 20,000 on issuer platforms.[12] The recent popularity of US underlyings in the Swiss structured product market has been attributed to the rising share of younger investors (younger than 45 years).[13] Studying Swedish household data, Calvet et al. (2019) find the mean investor to be 55 years old with an interdecile range of 35 years. Overall, this suggests a fairly heterogeneous investor base.

There exist different types of structured products whose synthetic payoff profiles cater to specific beliefs about future market performance. However, during the low interest

active yield-seeking documented in Lian et al. (2019).

[12] See, e.g., https://structuredproducts-ch.leonteq.com/ and https://www.deritrade.com/en, respectively.

[13] See, e.g., https://www.finanzen.ch/nachrichten/aktien/strukturierte-produkte-warum-der-anteil-an-us-underlyings-zunimmt-bx-swiss-tv-1029893848 (in German).

rate environment following the Great Recession, so-called yield enhancement products (YEPs) have emerged as the most popular product type (see Section 2.2.2). To illustrate the workings of YEPs, we first provide a prototypical example before describing the respective market in more detail.

2.2.1 An Example

YEPs are designed to allow investors to benefit from sideways-moving or slightly rising markets. They consist of two main components: (i) a fixed rate bond, and (ii) a short put option. From an investor's perspective, YEPs' upside potential is limited to their fixed coupon (headline rate), which, financed by the put premium, is, however, much higher than the prevailing risk-free rate. YEPs' non-participating upside is contrasted by their unlimited downside risk: in case the embedded put option expires in-the-money, investors forfeit the pre-paid principal and receive the low performing underlying instead. YEPs' final cash-flows thereby either depend on one single underlying or on a basket of underlyings. Crucially, in the latter case, only the *worst* performing underlying is payoff-relevant. This is commonly referred to as "worst-of" payoff profile.

The structural differences between distinct types of YEPs stem from the kind of shorted put option, i.e., plain vanilla vs. exotic puts. A particularly prominent type of YEPs are barrier reverse convertibles (BRCs), whose embedded option position consists of a short "down-and-in" European put. Specifically, such barrier options get activated when at least one underlying hits a predefined lower barrier, typically expressed in percentage of the option's strike price. Figure 2.2 illustrates the payoff diagram of a "Single" BRC based on one single underlying and a "Multi" BRC based on multiple underlyings, respectively. In the absence of a barrier event until maturity, BRC investors are repaid the coupon plus principal. In contrast, upon activation of the barrier put, the principal is converted into holdings of the *worst* performing asset (at a predefined ratio). In this case, investors' payoff equals the coupon plus the minimum of (i) the payoff-relevant underlying value at maturity and (ii) the principal. Given Multis' higher down-side risk, they generally offer investors higher coupons, ceteris paribus.

Table 2.1 provides the corresponding specifications of two exemplary BRCs issued by the same Swiss bank on May 26, 2011. Both BRCs presented in Table 2.1 exhibit typical attributes, i.e., equities as underlying assets and a short-term duration of approximately one year. The Multi's higher risk due to multiple underlyings is contrasted with a higher fixed coupon and a lower barrier. For the Single, investors start to participate in the losses

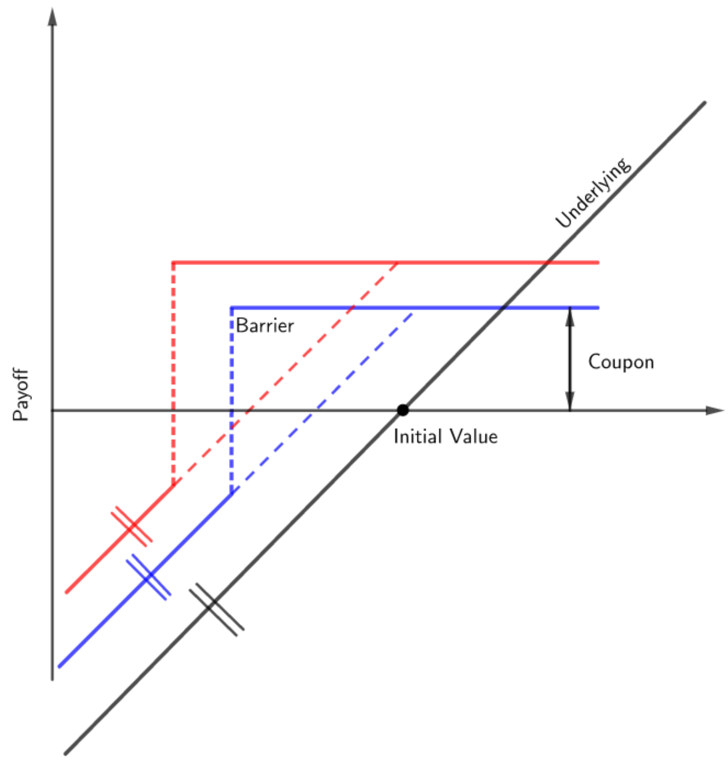


Figure 2.2: **Payoff profiles of Barrier Reverse Convertibles**

Figure 2.2 displays the payoff profiles of barrier reverse convertibles (BRCs) with one underlying asset (blue) and multiple underlying assets (red), respectively. The solid 45-degree line denotes the value of the payoff-relevant underlying at maturity. Vertical dashed lines indicate the respective barrier levels. The distance between the x-axis and the colored horizontal lines indicates the respective coupon payments, which do not depend on the performance of the underlying(s). If the price of at least one underlying hits the barrier before maturity, the product's principal is converted into holdings of the worst performing underlying (at a predefined ratio). In this case, the final payoff is capped at par (initial value) plus coupon.

if the underlying Microsoft shares fall by at least 20% following the initial fixing date. For the Multi, investors are protected as long as the worst performing stock falls by less than 35%. However, the ultimate question is, whether these more attractive features sufficiently compensate for the Multi's higher inherent risk. The respective margin estimates provided in Table 2.1 indicate the opposite. We systematically investigate this in Section 2.5.

Table 2.1: **Two exemplary barrier reverse convertibles**

Table 2.1 shows the product specifications of two BRCs issued on May 26, 2011. The second column provides the specifications for a BRC with one underlying ("Single"). The third column provides the specifications for a BRC with three underlyings ("Multi"). Product specifications include: product ISIN, underlying stocks and tickers, coupon per annum, barrier in percentage of underlying values at fixing, and time to maturity in calendar days. The final row provides the estimated margin at issuance (see Section 4 for details).

	Single	Multi
ISIN	CH0127927132	CH0125720794
Underlying(s)	Microsoft (MSFT)	Microsoft (MSFT)
		General Electric (GE)
		Newmont Mining (NEM)
Coupon (p.a.)	7.5740%	10.8791%
Barrier	80%	65%
Time to maturity	386 days	358 days
Estimated issuer margin	1.448%	4.966%

2.2.2 Market Overview

The Swiss market for retail structured products is one of the largest worldwide, with a total turnover amounting to CHF 331bn in 2018. According to the Swiss Structured Product Association (SSPA), YEPs accounted for 46% of sales volume during the same year, most of which were BRCs.[14]

Strikingly, the popularity of YEPs is not limited to Switzerland. Across all major European markets, YEPs represented more than 59% of all exchange-listed investment products by the end of 2018.[15] Similarly, in the US, with more than 40% of issuance volume, YEPs constitute the largest and fastest growing class among all retail structured products (Vokata, forthcoming).

Not surprisingly, this substantial market growth has also drawn the attention of var-

[14]See the Swiss Structured Products Association (SSPA) Q4 2018 market report available via https://www.svsp-verband.ch/en/market-report/2019/.

[15]See the European Structured Investment Products Association (EUSIPA) Q4 2018 market report available via https://eusipa.org/category/press-releases/.

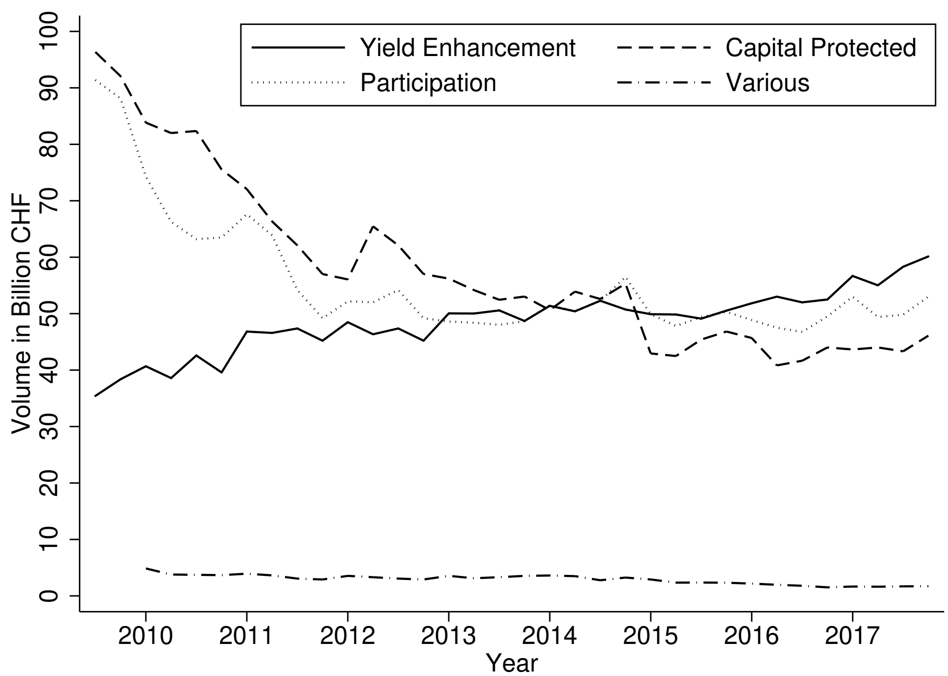


Figure 2.3: **Outstanding volume of structured products in Switzerland**

Figure 2.3 illustrates the evolution of outstanding volume (in bn CHF) of structured products in Switzerland between the third quarter of 2009 and the fourth quarter of 2017. Sources: Market reports provided by the Swiss Structured Product Association (SSPA) and the European Structured Investment Products Association (EUSIPA).

ious national regulators. For instance, already in 2007, the Swiss regulator outlined the minimum product information that issuers are required to provide to investors (Swiss Bankers Association, 2007). Moreover, several regulatory reports have pointed out the potential exploitation of information asymmetries between issuing banks and relatively inexperienced retail investors.[16]

Contrary to recent years, YEPs have not always been this popular among retail investors. For the Swiss market, Figure 2.3 displays the evolution of outstanding volumes across the four categories of investment structured products between 2009 and 2017. Besides YEPs, the two main categories are "Capital Protection" and "Participation" prod-

[16] See, for instance, the speech by SEC Commissioner Luis A. Aguilar in April 2015, available via https://www.sec.gov/news/speech/regulators-working-together-to-serve-investors.html. Similarly, the report on structured products by the British regulator, the Financial Conduct Authority, concludes that retail investors do not sufficiently understand payoff profiles that depend on the performance of underlying assets (Financial Conduct Authority, 2015).

ucts.[17] Importantly, in sharp contrast to YEPs, neither of the alternative categories offer a performance-independent fixed coupon. Figure 2.3 clearly shows how YEPs' outstanding volume steadily increased, while the volume of capital protection and participation products sharply declined after the Great Recession.

Lastly, we take a closer look at the issuer composition in the Swiss market for YEPs. The majority of products are issued by large and medium Swiss banks, but also by multinational investment banks and boutique providers of investment solutions.[18] Panel A in Figure 2.10 in the Appendix displays the YEP market share, measured by turnover, of all issuers that are among the top five in at least one year within our sample period. The total number of issuers is sizeable, with a yearly average of 23.4. Clearly, substantial changes in revenue shares occur over time, e.g., only three banks (Vontobel, Julius Baer, and the Zurich Cantonal Bank (ZKB)) managed to maintain a turnover share of at least 5% in each year. Panel B in Figure 2.10 depicts the evolution of the corresponding Herfindahl index, which, on average, equals 0.14, i.e., indicating an unconcentrated and competitive industry. The index also shows a slightly decreasing trend, i.e., hinting at a further increase in competition.

We interpret these market statistics as suggestive evidence for considerable competitive pressure among YEP issuers when it comes to attracting retail capital. This interpretation is further underpinned by the introduction of a multi-issuer platform in 2014.[19] In essence, for a given product, the platform allows investors to easily compare price quotes of up to eight issuers (including Vontobel, ZKB, and UBS). Since adoption, the platform has grown continuously, raising up to CHF 8.2bn in 2019.

2.3 Experiment

Initially, the rise in BRC issuance following the 2009 drop in interest rates was equally distributed between Singles and Multis (see Figure 2.3). However, starting from 2014, both the number and the volume of newly issued Multis have increased substantially, while

[17] Capital protection products allow investors to partially participate in rising underlying prices, while protecting them against capital losses. As the name suggests, participation products generally offer full or even progressive participation, while exposing investors to unlimited losses. For a concise overview, see, e.g., the SSPA Swiss Derivative Map 2019, available via https://www.svsp-verband.ch/wp-content/uploads/2019/01/SVSP_Faltblatt_205x297_2019_EN.pdf.

[18] See Table 2.19 in the Internet Appendix for a detailed overview of all issuers in our final sample.

[19] For details, see https://www.deritrade.com/en. A short introductory video (in German), using the case of a Single BRC, is available via https://www.youtube.com/watch?v=HO024UgdsDw.

the respective statistics of Singles started to decline. To investigate potential demand-side drivers behind this pattern, we first conduct a laboratory experiment that isolates (i) the effect of interest rate levels on participants willingness to invest in BRCs, (ii) the accuracy of their risk-return assessments for both Singles and Multis, and (iii) potential biases affecting participants' respective fair value estimations. We furthermore control for the effect of overall investment risk (volatility), risk preferences, and personality traits such as overconfidence (Barber and Odean, 2001; Biais, Hilton, Mazurier, and Pouget, 2005).

2.3.1 Design

The experiment was fully computerized using z-Tree (Fischbacher, 2007). For the main task, we created two synthetic product types mimicking the payoff structure of typical BRCs. In particular, participants were presented with synthetic "Singles" whose payoffs depended on the evolution of *one* underlying stock as well as synthetic "Multis" whose payoffs depended on the evolution of the *worst* performing of two underlying stocks.[20] To examine both interest rate and general investment uncertainty effects, we use a 2×3 (2) design (two volatility treatments and three (two) risk-free rate treatments).[21] Table 2.11 in the Appendix summarizes the different treatments.[22] In each experimental session, participants went through all treatments, with each treatment corresponding to one of six (four) independent rounds. The ordering of treatments was fully randomized between sessions. In each of the six (four) rounds, participants were given the chance to either invest in a Single or in a Multi, or, alternatively, safely store their money at the risk-free interest rate. Table 2.12 in the Appendix provides an overview of all parameters used across rounds. Importantly, our design allows for both a between and within-subject analysis. The latter enables us to control for idiosyncratic attributes in participants' behavior.

At the beginning of each round, participants were endowed with initial wealth amount-

[20] Designing synthetic products instead of using real BRCs has two advantages. First, it allows us to control each parameter separately and thereby greatly simplifies effect identification. Second, we avoid potential confounding effects due to participants' different levels of expertise about real stock markets.

[21] Early sessions only consisted of two (positive vs. negative) risk-free rate treatments.

[22] In a second part of the experiment, we also introduced a treatment with risk-adjusted coupons. Specifically, in this part, coupons were chosen such that both Singles and Multis had identical fair values assuming risk neutrality. While the general underestimation of Multis' correlation risk (see below) prevails, there is no significant difference between the willingness-to-pay for Singles vs. Multis. This result is in line with a higher subjective discount applied to Multis relative to Singles.

ing to 130 Experimental Currency Units (ECU), which they could invest freely.[23] Moreover, all participants received identical information about the products available for investment and the general investment environment, i.e., the prevailing risk-free rate and volatility level. To limit the complexity of the task, Multis' underlying asset prices always evolved independently of each other, which was also emphasized in the up-front provided information. To further facilitate participants' evaluation of the available products, the software calculated expected final payoffs based on participants' estimates of (i) the probability of a barrier event and (ii) the expected value of the payoff-relevant underlying conditional on such a barrier event.

At the first stage of each round, participants had to separately indicate their willingness-to-pay (WTP) for both Single and Multi. To elicit individuals' WTP, we employed the seminal, incentive-compatible mechanism proposed by Becker, DeGroot, and Marschak (1964). Specifically, for an extensive list of possible prices,[24] participants had to indicate whether or not they are willing to buy the product at hand. The actual price for each product was then randomly drawn from this predetermined price list (with uniform probabilities). Whenever the randomly drawn price was lower or equal to participants' maximum WTP, they were allocated the product in return for the randomly determined price. Any remaining wealth was automatically invested at the risk-free rate. In contrast, whenever the random price was higher than participants' WTP, their entire wealth was invested at the risk-free rate by default. To ensure that participants evaluated both product types independently, the price draw was only executed for one randomly chosen product in any round. Finally, participants always had the option to opt out of investing in BRCs altogether and, *independent* of the random price, invest all their wealth at the prevailing risk-free rate.

At the second stage of each round, after each participant's investment decision had been implemented, actual payoffs were determined and participants' final wealth was calculated. In addition, the price path realizations of the underlying assets were displayed and the corresponding scenario (occurrence vs. absence of barrier event) was indicated. All rounds were entirely independent of each other, i.e., at the beginning of every round, participants' initial wealth was reset to ECU 130.

Finally, after concluding the main task, we elicited participants' risk aversion, following Holt and Laury (2002), as well as their degree of overconfidence in judgment, following

[23] In a subsample, participants were endowed with ECU 140 instead. However, we find no significant effects associated with this slight increase in initial endowments.

[24] The price list ranged from a minimum price of ECU 60 to the highest achievable payoff of ECU 117.

Alpert and Raiffa (1982).

2.3.1.1 Procedural Details

The experiment was conducted in March and October 2018 at the computer laboratory of the Department of Banking and Finance at the University of Zurich. We ran the experiment with seven different cohorts, resulting in a sample of 125 undergraduate and postgraduate finance students. All participants had some basic training in derivative securities.[25] Table 2.17 in the Internet Appendix provides the summary statistics across all participating individuals. On average, our participants are 23 years old, with a slight majority of females (68) over males (57). Around one third consider themselves familiar with structured products (self-reported).

To alleviate low-stake incentive concerns and to induce sufficient risk aversion, following, e.g., Isaac, Walker, and Williams (1994), Selten, Mitzkewitz, and Uhlich (1997), Biais et al. (2005), and Williams (2008), participants' final wealth from one randomly selected round was converted into points that counted towards their final grade. The written instructions (see Internet Appendix) contained various comprehension questions that controlled participants' understanding of the task. Participants were only allowed to proceed to the practice round after they had answered those questions correctly. If necessary, further explanations were provided by the experimenter. On average, one session lasted about 90 minutes.

2.3.2 Experimental Results

We first describe the results at an aggregate level before turning to a detailed discussion of the different treatment effects and the influence of participants' personal traits on product margins.

2.3.2.1 Implied Margins

Table 2.13 in the Appendix presents summary statistics of the main experimental variables across treatments. On average, participants exhibit a higher WTP for Multis relative to Singles.[26] Table 2.13 also shows that participants correctly assign a higher likelihood

[25]Therefore, ex ante, we consider it plausible that actual retail investors are as likely to suffer from potential behavioral biases.

[26]Conservatively, whenever participants' maximum WTP is not uniquely defined (due to multiple switching points in the elicitation task), we set it equal to the lowest value. Note, throughout our

of a barrier event to the case of multiple underlyings. To assess the accuracy of their risk assessment, we measure the difference between true probabilities and participants' respective estimates. On average, participants slightly overestimate Singles' inherent risk of a barrier event by 2.25%, whereas they substantially *underestimate* the corresponding risk for Multis by 6.18%.

To compare revealed WTP levels across products and participants, we compute each product p's margin implied by participant i's WTP as

$$\text{Margin}_{pi} = \frac{\text{WTP}_{pi} - \text{FV}_p}{\text{WTP}_{pi}},$$

where FV_p denotes product p's fair value under risk neutrality. Hence, a product's implicit margin is defined as the percentage difference between participants' product-specific WTP and the product's expected cash flow discounted at the prevailing risk-free rate. Recalling Multis' higher inherent down-side risk, this approach represents a conservative fair value comparison of Multis relative to Singles.

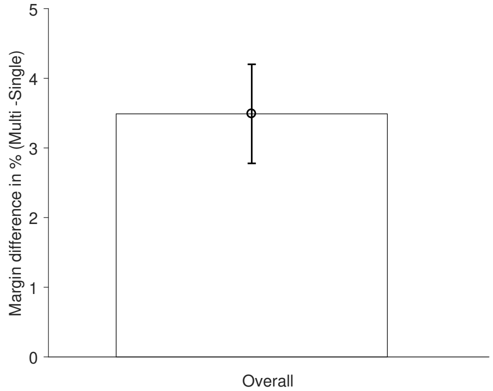
We find participants to overvalue Multis relative to Singles. Panel A in Figure 2.4 shows the average difference in margins between Multis and Singles. Overall, the implicit margin for Multis is 3.49% higher than for Singles. A two-sided t-test strongly rejects the null hypothesis of identical margins (p-value < 0.01).

Next, to control for confounding effects, we regress product margins on a Multi-Dummy (equal to one for Multis) while controlling for participants' investment decisions, volatility levels, and the risk-free interest rate. Table 2.2 shows the results of different regression specifications. In the first model, we include participant fixed effects, whereas, in the second model, we control for participant characteristics such as gender, age, risk preferences, and overconfidence.

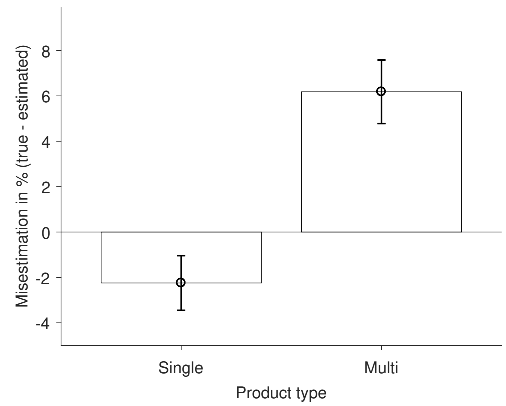
For both specifications, we find that Multis are associated with significantly higher margins (p-value < 0.01). Moreover, while, in the first model, interest rates have no significant effect on margins, interest rates are *positively* correlated with margins in the second model. The latter result, however, may be caused by certain participants' failure to coherently discount their fair value estimates (WTP) across interest rate treatments. When controlling for participant fixed effects, contrary to Célérier and Vallée (2017), we find no evidence that interest rates affect margin *levels*.

Intuitively, we find margins to be decreasing in participants' risk aversion and increas-

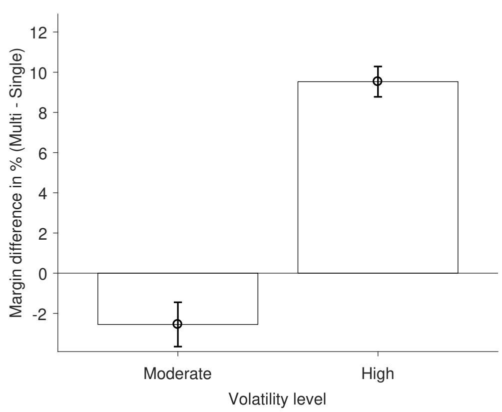
experimental analysis, we do not discard one single observation.



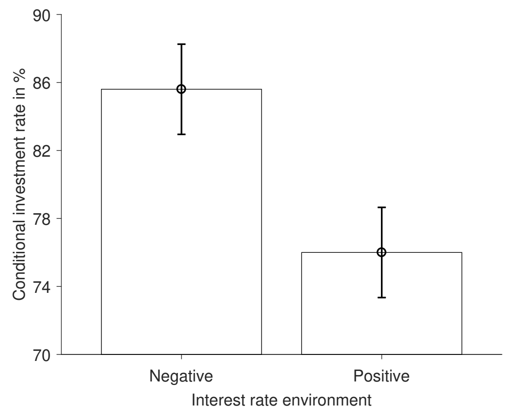
(a) **Panel A: Margin difference**



(b) **Panel B: Probability misestimation**



(c) **Panel C: Volatility levels**



(d) **Panel D: Investment rate**

Figure 2.4: **Main experimental results**

Panel A shows the average margin difference between Multis and Singles, i.e., Multi minus Single, across all rounds. Panel B shows the average probability misestimation for both product types across all rounds. We measure probability misestimation as the difference between the true probability minus participants' estimated probability of a barrier event. Panel C shows the difference in margins under moderate (13.7% per unit of time) and under high volatility (27.4%) of the underlying asset(s), respectively. Panel D shows the investment rate, i.e., the conditional willingness to invest in either product, for different interest rate environments. Error bars represent standard errors.

ing in their level of overconfidence. Figure 2.11 and Figure 2.12 in the Appendix provide scatter plots with the corresponding best linear fits. Interestingly, Figure 2.12 suggests that participants' degree of overconfidence substantially drives the margins of Multis but does not significantly affect the margins of Singles.

Table 2.2: **Margins of Singles and Multis in the experiment**

Table 2.2 displays the coefficients of OLS regressions with product margins as the dependent variable. In the first specification, we regress margins on a *Multi-Dummy* (equal to one for Multis) and control for participants' investment decision, high volatility level, positive interest rates, as well as participant and round fixed effect. In the second specification, we add participant characteristics, including risk preferences and overconfidence. Standard errors are reported in parentheses and are clustered at the participant level. * , ** , and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1) Margin	(2) Margin
Multi-Dummy	3.490***	3.490***
	(1.055)	(1.057)
Invest Decision	13.358***	25.761***
	(3.124)	(3.991)
Vola-Dummy	24.374***	24.951***
	(1.689)	(1.734)
Interest-Dummy	-1.804	3.107**
	(1.298)	(1.491)
Male		4.244
		(3.161)
Age		0.037
		(0.252)
Risk Preference		-1.996**
		(0.788)
Overconfidence		13.723*
		(7.633)
Constant	Yes	Yes
Subject FE	Yes	
Round FE	Yes	Yes
Observations	1,212	1,212
R^2	0.742	0.400

2.3.2.2 Interest Rates and Willingness to Invest

Next, we isolate the impact of different interest rates on participants' willingness to invest in BRCs. Via our interest rate treatment, we introduce different spreads between products' coupons and the prevailing risk-free interest rate (see Table 2.11 in the Appendix). Expanding Lian et al. (2019), who focus on a simple risky asset, we are particularly interested in how varying risk-free rates affect the proportion of participants who are willing to invest in either Singles or Multis as opposed to the risk-free alternative.

For each participant, we compute the conditional investment rate as the proportion of rounds during which she decided to opt into the investment (bidding) process. Panel D in Figure 2.4 shows average investment rates for the positive (3% per time unit) and negative (-2%) interest environment, respectively. A Wilcoxon signed-rank test rejects the null hypothesis of identical investment rates (p-value < 0.01). While the same holds true for the difference between positive and zero interest rates (p-value < 0.01), we find, however, no significant difference between zero and negative interests. Hence, our results indicate that very low but non-negative risk-free rates are sufficient to induce yield-reaching behavior (Bordalo et al., 2016).

Table 2.3 presents the results from corresponding logistic regressions. The estimated coefficients are of economic significance: under positive interest rates, the proportion of participants who are willing to invest in either Singles or Multis declines, on average, by 11.7% relative to zero or negative interest rates. Note, none of the other variables significantly impact participants' investment propensity.

2.3.2.3 Probability Misestimation and Volatility Levels

Panel B in Figure 2.4 shows that participants are relatively accurate in assessing the probability of a barrier event for Singles. However, they significantly underestimate the corresponding risk for Multis. On average, participants slightly overestimate Singles' probability of a barrier event by 2.25%, while, in the case of Multis, they significantly underestimate the corresponding probability by 6.18%. Importantly, the only explanation for this discrepancy lies in the inability to correctly account for the combination of multiple underlyings with a worst-of payoff structure. While participants sufficiently account for the risk induced by one single underlying, they clearly fail to do so in the presence of two underlying assets.

To investigate this finding further, we examine the correlation between participants' probability misestimation and the corresponding product margins. As expected, margins

Table 2.3: **Investment rate**

Table 2.3 displays coefficients of logistic regressions where the dependent variable is participants' conditional willingness to invest in either Singles or Multis (as opposed to the risk-free alternative). *Interest-Dummy* indicates rounds with positive interest rates. In specification (1), the raw effect of a positive risk-free rate is estimated, while specification (2) includes controls for a high volatility level and participant characteristics. Standard errors are reported in parentheses and are clustered at the participant level. * , ** , and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1) Invest Decision	(2) Invest Decision
Interest-Dummy	-1.322***	-0.722***
	(0.294)	(0.191)
Vola-Dummy	-0.216	-0.139
	(0.269)	(0.188)
Male		-0.171
		(0.343)
Age		-0.026
		(0.022)
Risk Preference		-0.020
		(0.096)
Overconfidence		-0.309
		(0.891)
Constant	3.362***	2.974***
	(0.423)	(0.995)
Subject FE	Yes	
Observations	606	606

strongly correlate with participants' misestimation. Specifically, when participants accurately estimate the probability of a barrier event, margins are close to zero, whereas, in the case of imprecise probability estimates, margins are significantly different from zero (correlation coefficient of 0.63, p-value < 0.01).

In line with this result, we find a higher volatility of the underlying asset(s) to increase the discrepancy in margins between product types. Naturally, a rise in volatility increases the likelihood of a barrier event and, hence, the risk of low payoffs. Therefore, ceteris paribus, the value of both Singles and Multis is a decreasing function in the underlying volatility level.[27] Strikingly, participants estimate both the probability of a barrier event and the conditional payoff quite accurately under moderate volatility (13.7% per time unit), whereas they experience substantial difficulties doing so under relatively high volatility (27.4%). Panel C in Figure 2.4 documents this finding. A two-sided t-test strongly rejects the hypothesis of no difference in margins between Singles and Multis in the high volatility environment (p-value < 0.01).

In sum, the magnitude of this documented risk misestimation more than suffices to explain the experimentally documented margin discrepancy between Singles and Multis. However, as indicated above, participants are, on average, risk-averse and, accordingly, bid somewhat prudently given their subjective probability estimates. For instance, while, under high volatility, average estimates would justify risk-neutral Multi margins of 20.3%, actual margins are "only" half as large (10.4% on average). This indicates that participants indeed demonstrate awareness of the investment task's difficulty but fail to fully correct for the bias in their risk estimates.

2.4 Field Data and Pricing Methodology

To contrast our experimental findings with evidence from the field, we investigate, in a second step, the term sheets of all barrier reverse convertibles publicly issued in Switzerland between January 2008 and December 2017.[28] The initial data set contains 47,080 BRCs. However, contrary to our experiment, a pricing model is required to estimate products' fair values. To ensure the highest possible quality of input variables, we focus on US equities with traded put options. Importantly, this allows us to rely on forward-looking market estimates of the underlying assets' volatility. Our final sample includes 4,460 BRCs on US stocks.[29] Table 2.19 in the Internet Appendix lists the top ten issuers of BRCs in our final sample as well as the number and type of products issued over time.

To obtain all input data for the pricing model, we rely on various databases. In addition to our BRC data set, which provides product information regarding the issuer, issue date, expiry date (maturity), coupon rate, barrier level, conversion rate, and the underlying assets, we get valuation inputs from the Center for Research in Security Prices

[27] More precisely, the value of the embedded (short) put option is an increasing function in the underlying volatility level.

[28] We thank Derivative Partners for providing us with the data.

[29] Table 2.18 in the Internet Appendix provides summary statistics of all BRCs in the initial data set.

(CRSP) and the Option Metrics' IvyDB US database. Finally, we obtain our proxy for the risk-free rate from Bloomberg (see below), which also provides data on issuance volumes. To merge data across sources, we use the name of the underlying assets and then their CUSIP numbers as identifiers. For all underlying assets, we find the closest name in OptionMetrics measured by the Levenshtein distance. We then validate each match and manually allocate name pairs that do not match perfectly.

2.4.1 Descriptive Statistics

Table 2.4 presents an overview of our final sample. In Panel A, we provide summary statistics of product characteristics. The average BRC in our sample offers an annual coupon of 9.29% on an accumulated notional of CHF 18.3 million. The average maturity is slightly below one calendar year, and the average barrier level is around 67% of the underlying stocks' value at fixing.[30]

The pricing model requires several input variables. To estimate the dividend yield of underlying stocks, we use data from CRSP. We assume that dividend yields remain constant over a product's lifetime and calculate the annual yield as the sum of dividend payments over the last twelve months (prior to issuance) divided by the stock's closing price (at issuance). Using Option Metrics data, we extract implied volatilities of underlying stocks (at issuance) from traded put options in two steps.[31] First, we search for the "closest" four options for each underlying asset, i.e., the put option with the closest lower (higher) strike price and the put option with the closest shorter (longer) maturity relative to the product's expiry date. Second, we bi-linearly interpolate the implied volatilities from the corresponding four options in the two-dimensional space of strike prices and maturities. If one or more of these four options are unavailable, we follow Henderson and Pearson (2011) and extract the implied volatility from the put option with the nearest expiry date and the closest strike price. Finally, to approximate the risk-free interest rate, we rely on the overnight index swap (OIS) rate provided by Bloomberg and match maturities via linear interpolation.

Panel B of Table 2.4 provides summary statistics of annualized input variables across all underlying assets in our final sample. The average dividend yield is 2.45%, and the

[30]Since we receive volume at issuance data from Bloomberg, we have volume data for 2,541 products, which we winsorize at the 5% level.

[31]As the put-call parity often does not hold in practice (see, e.g., Figlewski and Webb, 1993, Amin, Coval, and Seyhun, 2004, and Ofek, Richardson, and Whitelaw, 2004), we restrict ourselves from using call options to infer implied volatilities.

Table 2.4: **Summary statistics of final sample**

Table 2.4 reports summary statistics of product characteristics (Panel A) and pricing model inputs (Panel B) for all barrier reverse convertibles in our final sample. *Coupon p.a.* (%) is the product's annual coupon rate (extracted from its payoff description). *Barrier level* (%) is the barrier level of the product's embedded put option in percentage of underlying values at fixing. *Maturity* (days) is the product's time to maturity at issuance. *# of underlyings* indicates the number of payoff-relevant underlying asset(s). *Volume (mil. CHF)* is the issued volume. Valuation inputs are reported as annualized averages over all underlying assets (see text for details). Panel C presents summary statistics of the various linear correlation estimates (i.e., simple estimation ($Correlation_{Hist}$), the Ledoit and Wolf (2004) approach ($Correlation_{LW}$), and the Chen, Wiesel, Eldar, and Hero (2010) approach ($Correlation_{OAS}$)) and the frequency of return *comovement* (see text for details). The sample consists of 4,460 products issued between January 2008 and December 2017.

Panel A: Product characteristics							
	Mean	Std	Min	Q1	Median	Q3	Max
Coupon p.a. (%)	9.29	3.53	0.00	6.94	8.65	10.88	57.34
Barrier level (%)	66.65	9.59	39.00	59.00	69.00	75.00	90.00
Maturity (days)	355	104	60	357	358	386	1,093
# of underlyings	1.83	0.98	1	1	1	3	4
Volume (mil. CHF)	18.31	10.17	3.00	10.00	20.00	30.00	40.00
Observations	4,460						
Panel B: Valuation inputs							
Dividend yield (%)	2.45	4.53	0.00	0.51	1.71	2.71	18.12
Implied vola. (%)	33.42	11.72	13.53	25.15	31.34	38.97	123.37
Risk-free rate (%)	0.51	0.49	0.06	0.14	0.32	0.60	3.09
Observations	4,460						
Panel C: Correlation and comovement estimates							
$\text{Correlation}_{Hist}$	0.449	0.214	-0.021	0.290	0.442	0.575	0.912
Correlation_{LW}	0.383	0.245	0.000	0.207	0.389	0.531	0.884
Correlation_{OAS}	0.431	0.216	-0.014	0.271	0.424	0.558	0.895
Comovement (%)	67.02	7.69	51.88	61.94	65.59	70.16	87.85
Observations	1,932						

average implied volatility is 33.42%. The latter is relatively high compared to long-term average volatility levels. The average risk-free rate over our sample period is 0.51%.

2.4.1.1 Measuring Correlations between Underlying Assets

To evaluate the fair values of issued Multis, we additionally require an estimate of the correlations between underlying assets. Since there exists no traded instrument to reliably infer markets' correlations expectation, we have to independently estimate the underlying correlation structure. As noted above, the correlation among underlying assets crucially affects Multis' fair value: the *lower* the correlation, the *higher* the probability of a barrier event. Hence, to account for possible measurement errors, we complement our simple correlation estimation based on one year of daily log returns with two additional estimation approaches: (i) the shrinkage estimator of Ledoit and Wolf (2004) and (ii) the oracle approximating shrinkage (OAS) method proposed by Chen et al. (2010). Results of all three approaches are reported in Panel C of Table 2.4 (denoted by $\text{Correlation}_{Hist}$, Correlation_{LW}, and Correlation_{OAS}, respectively). As a robustness check, we also apply these estimation approaches to six and 24 months of pre-issuance daily returns, respectively, with no substantial effect on the distribution of estimated correlations in either case.[32]

2.4.2 Singles versus Multis

Before examining the relation between product types and issuer margins, we separately investigate the product characteristics of Singles and Multis, respectively. Given that, by design, Multis carry a higher risk than Singles due to their embedded worst-of payoff profile, we expect Singles and Multis to differ in their product specifications to compensate for the latter's higher downside risk. The summary statistics of the respective product specifications are reported in Table 2.5.

Our final sample consists of 2,528 Singles and 1,932 Multis. Note, compared to the total number of BRCs in our data set, we lose somewhat more observations for Multis than for Singles. This is due to the higher restrictions on pricing data availability for BRCs with multiple underlyings. In our final sample, Multis are, on average, based on 2.92 underlying stocks. The average maturity of both product types is slightly shorter than one year. Multis offer, on average, a 1.76 pp. higher annual coupon, while their

[32]Detailed summary statistics are available from the authors.

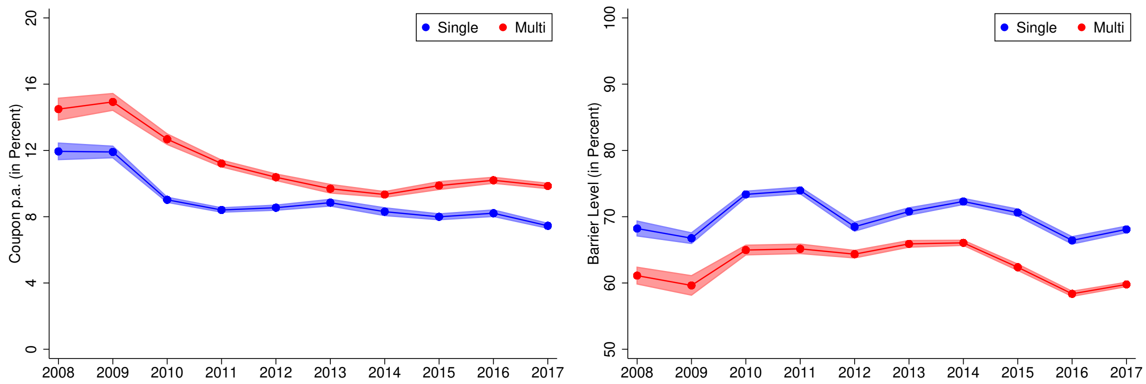
Table 2.5: **Comparison between Singles and Multis**

Table 2.5 reports summary statistics of product characteristics and pricing model inputs for Singles and Multis, respectively. *Coupon p.a.* (%) is the product's annual coupon rate (extracted from its payoff description). *Barrier level* (%) is the barrier level of the product's embedded put option in percentage of underlying values at fixing. *Maturity* (days) is the product's time to maturity at issuance. *# of underlyings* indicates the number of payoff-relevant underlying asset(s). Estimated valuation inputs are reported as annualized averages over all underlying assets (see text for details). The subsample of Singles (Multis) consists of 2,528 (1,932) products. The total sample consists of 4,460 products issued between January 2008 and December 2017. t-statistics are reported in parentheses. * , ** , and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Single			Multi				
	Mean	Median	Std	Mean	Median	Std	Δ Mean	t-stat
Coupon p.a. (%)	8.53	7.86	3.45	10.29	10.00	3.38	-1.76***	(-17.04)
Barrier level (%)	70.01	70.00	9.56	62.25	62.00	7.66	7.76***	(30.08)
Maturity (days)	353.56	360	77.54	355.73	358	131.59	-2.17	(-0.64)
Divid. yield (%)	2.19	1.54	8.22	2.79	1.82	6.51	-0.60**	(-2.71)
Implied vola. (%)	33.42	30.93	12.78	33.43	31.84	10.17	-0.01	(-0.02)
# of underlyings	1	1	0	2.92	3	0.34		
Observations	2,528			1,932				

barrier level is 7.76 pp. lower. Both differences are statistically significant at the 1% level. Thus, in both dimensions, Multis' specifications are *unconditionally* more attractive than those of Singles. Notably, however, both product types are based on underlying assets with equally high implied volatility levels (around 33% per annum) as well as comparable levels of dividend yields. In total, our final sample covers 172 underlying stocks. Table 2.15 in the Appendix provides an overview of the 30 most frequently used equities for Singles and Multis, respectively.

Figure 2.5 plots the time trend of the two deviating product characteristics for both product types. Panel A shows that the difference between average coupons (headline rates) remains fairly stable over time. Panel B illustrates that the same holds for the respective average barrier levels. Interestingly, we observe that annual coupons decrease for both Singles and Multis. This finding can be reconciled with the decreasing trend in



(a) **Panel A: Coupon (headline rate)**

(b) **Panel B: Barrier level**

Figure 2.5: **Main product specifications of Singles and Multis over time**

Figure 2.5 shows the average annual coupon (headline rate in %, Panel A) and the average barrier level in percent of the underlying values at fixing (Panel B) for Singles (Multis) in blue (red), between January 2008 and December 2017. Shaded areas indicate one standard-error confidence intervals. The subsample of Singles (Multis) consists of 2,528 (1,932) products.

interest rates over our sample period.

2.4.3 Pricing Model

Following the literature (see, e.g., Henderson and Pearson, 2011, and Célérier and Vallée, 2017), our pricing approach builds on the closed-form solution for down-and-in European put options on a single underlying under the assumptions of Black and Scholes (1973). In this model, Singles can, therefore, be priced in closed form. Multis, however, cannot. Hence, to derive an accurate pricing model for Multis, we proceed as follows: first, we price Singles following the above closed-form solution (the pricing formula is provided in the Appendix). Second, we repeat the pricing of Singles, but now rely on a standard Monte Carlo method instead. We then verify the accuracy of this numerical method by comparing the respective prices.[33] Finally, after ensuring that neither sampling nor discretization errors systematically distort the values of numerically priced Singles, we apply the same Monte Carlo method for the pricing of Multis.

[33]See Table 2.20 in the Internet Appendix for a comparison of both pricing approaches. The results of the Monte Carlo procedure are based on 365 yearly time steps and 50,000 price path simulations for each underlying asset.

Our pricing approach, although straightforward, demands some elaboration. It is well known that the assumptions of constant volatility and continuous price paths (i.e., absence of jumps) in Black and Scholes (1973) do not hold in reality. However, both these features generate leptokurtic distributions of the underlying asset returns. Thus, given that BRCs are composed of deep out-of-the-money put options, both stochastic volatility and price jumps increase the (absolute) value of the embedded short option position and thereby decrease the value of the BRC as a whole. Therefore, our pricing methodology provides conservative fair value estimates for both Singles and, in particular, Multis.

2.5 Field Evidence

In the following, we present the empirical results from our field data analysis. First, we report estimated BRC margins at issuance and investigate their determinants for both Singles and Multis, respectively. Second, we compare issuance margins to the realized ex-post performance of each product type. Third, we analyze the time dynamics of both issuer margins and product specifications in the context of supply competition. Finally, we investigate the potential role of investors' perceptional biases in the cross section of Multi margins and with respect to frequent underlying combinations.

2.5.1 Issuer Margins

To estimate issuer margins as of the issuance date, we calculate the fair value of each product according to the pricing procedure described in Section 2.4.3. To control for correlation measurement errors, we compute the margins of Multis using all three correlation estimation approaches introduced in Section 2.4.1. Following the literature (see, e.g., Henderson and Pearson, 2011, Ammann et al., 2018, Egan, 2019, and Vokata, forthcoming), we calculate the issuer margin for every product as follows:

$$\text{Margin}_{pt} = \frac{\text{IP}_{pt} - \text{FV}_{pt}}{\text{IP}_{pt}},$$

where Margin_{pt} is the issuer margin for product p at issuance date t, IP_{pt} denotes the corresponding issue price (including fees and commissions),[34] and FV_{pt} its fair value as

[34]Most BRC issuers in Switzerland do not charge explicit fees or commissions.

implied by our pricing model.[35]

Table 2.6, Panel A, reports summary statistics of estimated issuer margins for both Singles and Multis. We find an average margin for Singles of 2.0% and an average margin for Multis between 4.1% and 4.4%, depending on the correlation estimation approach. Moreover, Figure 2.6 illustrates the evolution of average margins (based on simple correlation estimations) for both product types over our sample period. Generally, issuer margins exhibit a decreasing time trend (see Subsection 2.5.3 for regression analysis). In comparison with the literature, our estimates are similar but slightly lower than those documented for the US market (see Henderson and Pearson, 2011, Egan, 2019, and Vokata, forthcoming).

To analyze this discrepancy in issuer margins between Singles and Multis, we run several regressions. In Panel B of Table 2.6, we regress margins on a Multi-Dummy (equal to one for Multis), including issuer fixed effects, month fixed effects, and double-clustered standard errors:

$$\text{Margin}_{pt} = \beta_0 + \beta_1 \text{Multi-Dummy}_p + \gamma \text{FE}_{Issuer} + \delta \text{FE}_{Month} + \epsilon_{pt},$$

where β_1 is the main coefficient of interest, while FE_{Issuer} denotes the issuer fixed effect and FE_{Month} the month fixed effect, respectively. Consistent with our experimental findings, the results in Panel B show significantly higher margins for Multis than for Singles across all model specifications. Moreover, when controlling for issuer and month fixed effects (even columns), the difference in margins between Singles and Multis increases to approximately 2.9 pp. on average. Table 2.21 in the Internet Appendix repeats the above analysis while controlling for product characteristics and the risk-free rate. Given our pricing model, all coefficients exhibit the expected sign. In particular, we note (i) the relatively large Multi-Dummy coefficient, and (ii) the insignificant impact of the risk-free rate in the presence of a month fixed effect. For Multis, given the small variations in margins derived from the different correlation estimations, we focus in the following on the most conservative margin estimates based on simple historical correlations (Margin_{Hist}).[36]

[35]Note, our margin estimation abstracts from any hedging implementation costs, as we do not observe bid-ask spreads of BRCs' embedded barrier options, which are typically traded over-the-counter. Assuming hedging costs equal to ten percent of the option value (Muravyev and Pearson, 2016), our calculations suggest that the average hedging costs for Multis are less than 40 basis points higher than for Singles. Moreover, when focusing on the difference in margins between Singles and Multis, any potential exposure to foreign currency risk (notional) cancels out.

[36]All our results hold across correlation estimation approaches.

Table 2.6: **Issuer margins – Singles vs. Multis**

Table 2.6, Panel A, reports estimates of issuer margins for Singles and Multis, where margins for Multis are based on three different correlation estimation approaches. Panel B reports coefficient estimates from OLS regressions with issuer margins as dependent variable and a *Multi-Dummy* (equal to one for Multis) as main regressor of interest. In specifications (1) to (2), Multi margins are based on simple correlation estimations ($Margin_{Hist}$). In specifications (3) to (4), and (5) to (6), Multi margins are based on correlation estimations applying the Ledoit and Wolf (2004) ($Margin_{LW}$) and the Chen et al. (2010) ($Margin_{OAS}$) shrinkage method, respectively (see Section 2.4.1.1 for details). In (1), (3), and (5), raw effects of the *Multi-Dummy* are reported. In (2), (4), and (6), issuer and month fixed effects are added to the model specifications. The subsample of Singles (Multis) consists of 2,528 (1,932) products. The total sample consists of 4,460 products issued between January 2008 and December 2017. Standard errors are reported in parentheses and are clustered at the issuer and the month level. * , ** , and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Margins

	Single	Multi_{Hist}	Multi_{LW}	Multi_{OAS}
Mean	2.01	4.06	4.36	4.15
Median	1.37	3.25	3.52	3.37
Std	4.51	6.67	6.83	6.71
Observations	2,528	1,932	1,932	1,932

Panel B: Regressions on product type

	Margin_{Hist}		Margin_{LW}		Margin_{OAS}	
	(1)	(2)	(3)	(4)	(5)	(6)
Multi-Dummy	2.041***	2.749***	2.337***	3.067***	2.135***	2.851***
	(0.551)	(0.604)	(0.573)	(0.626)	(0.561)	(0.613)
Constant	2.019***	1.715***	2.019***	1.706***	2.019***	1.711***
	(0.163)	(0.266)	(0.163)	(0.275)	(0.163)	(0.270)
Issuer FE		Yes		Yes		Yes
Month FE		Yes		Yes		Yes
Observations	4,460	4,457	4,460	4,457	4,460	4,457
R^2	0.032	0.116	0.041	0.125	0.035	0.119

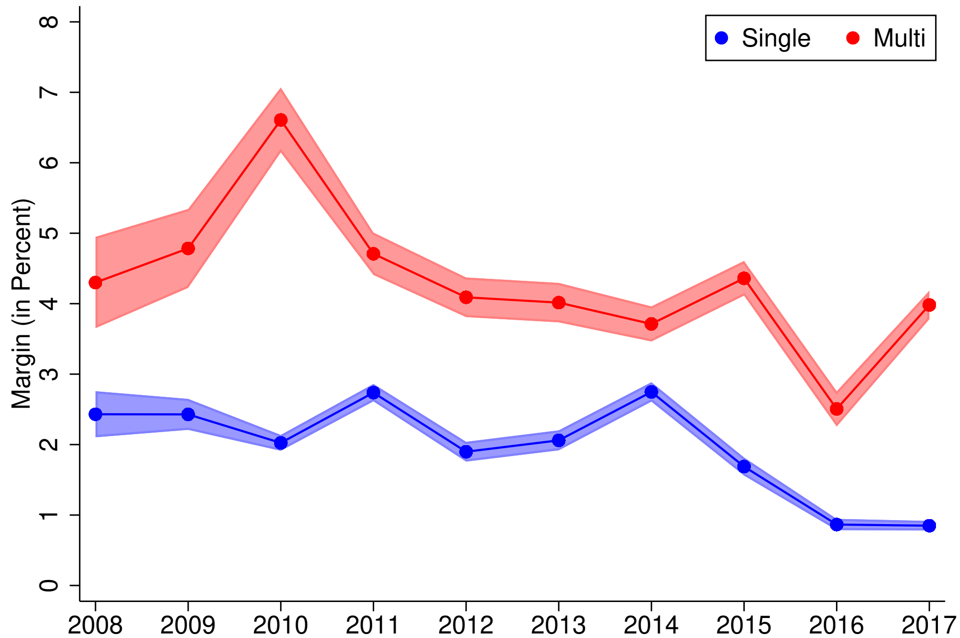


Figure 2.6: **Issuer margins of Singles and Multis over time**

Figure 2.6 shows average issuer margins for Singles (blue) and Multis (red) between January 2008 and December 2017. Margins are denoted in percent and calculated as:

$$\text{Margin}_{pt} = \frac{\text{IP}_{pt} - \text{FV}_{pt}}{\text{IP}_{pt}},$$

where Margin_{pt} is the issuer margin for product p at issuance date t, IP_{pt} denotes the corresponding issue price, and FV_{pt} its fair value as implied by our pricing model (using simple correlation estimations for Multis). Shaded areas indicate one standard-error confidence intervals. The subsample of Singles (Multis) consists of 2,528 (1,932) products.

2.5.1.1 Margin Drivers for Multis

For a better understanding of the discrepancy in issuer margins between Singles and Multis, we explore the relation between margins and product characteristics in more detail. As shown in Section 2.4.2, from an investor's perspective, the main product specifications, i.e., annual coupons and barrier levels, *unconditionally* favor Multis over Singles. Hence, those specifications cannot possibly explain the discrepancy in issuer margins. Consequently, the documented margin discrepancies must either stem from other product characteristics, such as implied volatilities of the underlying assets and their dividend yields, or must be driven by Multis' embedded correlation risk induced by their worst-of payoff structure.

To investigate how the interplay between Multis' worst-of design and the correlation of underlying assets affects issuer margins, we regress the margins of Multis with three underlying assets on product characteristics, including estimated underlying correlations. We fix the number of underlying assets at three to control for any further confounding effects of varying payoff contingencies. Importantly, Multis with three underlying assets constitute the "median Multi type" (see Table 2.5), representing approximately 88% of all Multis in our final sample. The results of these regressions are presented in Table 2.14 in the Appendix.

While controlling for coupon, barrier level, maturity, as well as underlyings' implied volatility and dividend yield, plus the prevailing risk-free rate, we find a significant negative relation between a Multi's margin and both its average and minimum correlation (across all three underlyings), respectively. Intuitively, a lower correlation among underlying assets, ceteris paribus, results in a higher margin, as the implied probability of a barrier event increases. Additionally, conditional on a barrier event, a lower correlation also increases the downside exposure borne by investors. The results in Table 2.14 imply that the lower the correlation among a Multi's underlying assets, the higher the associated margin for its issuer. Thus, also across Multis, product characteristics, e.g., headline rates and barrier levels, do *not* sufficiently compensate for higher correlation risk.

2.5.2 Ex-post Performance

So far, we have analyzed ex-ante, i.e., expected margins from the issuers' perspective.[37] Here, we report results on the ex-post, i.e., realized performance of both Singles and Multis from the investors' point of view. To get an *optimistic* estimate of BRCs' investment performance, we adjust realized returns only for the *risk-free* rate. This is likely to imply a favorable perspective on their ex-post returns, considering that the average retail investor is risk-averse (see our experimental evidence, or, e.g., Célérier and Vallée, 2017). Specifically, we compute each product's annualized log return as follows:

$$\text{Return}_{pt} = \frac{1}{(T-t)} \left[\ln\left(\frac{\text{Payoff}_{pT}}{\text{IP}_{pt}} \right) - r_t(T-t) \right],$$

[37] Note, under the premise that issuers hedge their exposure, these margins are actually locked in at the time of issuance.

where Return_{pt} is the log return of product p issued at t, Payoff_{pT} denotes its realized payoff at maturity T, IP_{pt} the product's issue price, and r_t the continuous risk-free rate at issuance.[38] Results are presented in Table 2.7.

Panel A in Table 2.7 reports summary statistics of ex-post performances for Singles and Multis, respectively. On average, Singles pay a yearly premium of 0.78% in excess of the risk-free rate. Strikingly, Multis' average annual return is negative, i.e., −1.62% when controlling for the risk-free rate. Across our sample, ex-post performances display considerable variation over time. Notably, during the crisis, investors in Multis, on average, lost close to one quarter of their initial investment.

Panel B in Table 2.7 again shows results from product-type regressions, this time with realized returns as the dependent variable:

$$\text{Return}_{pt} = \beta_0 + \beta_1 \text{Multi-Dummy}_p + \gamma \text{FE}_{Issuer} + \delta \text{FE}_{Month} + \gamma_{pt}.$$

In line with our regression analysis of estimated issuer margins in Section 2.5.1, we find a significant difference in ex-post returns between Singles and Multis, while controlling for both issuer and month fixed effects. The Multi-Dummy coefficient estimate in specification (2) indicates that Multis, on average, pay 2.6 pp. lower investment returns than Singles (p-value $= 0.012$).

Strikingly, on average, *absolute* differences between Singles and Multis are fairly similar for both ex-ante (estimated) margins (2.9 pp.) as well as ex-post (realized) returns (2.6 pp.). In other words, Multis' extra margin estimated at issuance closely matches the average extra return realized by their issuers. The deviations in levels likely stem from the risk-neutral discount rate that underlies the above calculation of realized returns. However, the resulting values square reasonably well with carefully beta-adjusted returns of Singles issued in the US (Vokata, forthcoming). Importantly, the similarity in margin differences corroborates the sufficient accuracy of our pricing model for comparing the profitability of Singles vs. Multis.

[38] To get annualized returns, the time difference between issuance date t and maturity T is measured in years here.

Table 2.7: **Ex-post performance of Singles and Multis**

Table 2.7 reports summary statistics of average realized returns (per year of issuance) for Singles and Multis, respectively (Panel A), and coefficient estimates from OLS regressions with realized returns as dependent variable and a *Multi-Dummy* (equal to one for Multis) as main regressor of interest (Panel B). The subsample of Singles (Multis) consists of 2,528 (1,932) products. The total sample consists of 4,460 products issued between January 2008 and December 2017. Standard errors are reported in parentheses and are clustered at the issuer and the month level. * , ** , and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Ex-post product returns

	Single		Multi	
	Mean (%)	N	Mean (%)	N
Issued in 2008	-7.80	68	-25.12	27
2009	11.75	114	14.71	38
2010	7.54	142	7.44	101
2011	-2.12	246	2.98	143
2012	0.91	283	-6.64	158
2013	0.64	295	-10.12	147
2014	-5.92	373	-16.22	267
2015	-0.57	335	-2.86	240
2016	6.82	317	6.86	328
2017	1.14	355	2.30	483
Full sample	0.78	2,528	-1.62	1,932

Panel B: Regressions on product type

	(1) Product return	(2) Product return
Multi-Dummy	-2.401*	-2.564**
	(1.245)	(0.932)
Constant	0.781	0.848**
	(0.530)	(0.387)
Issuer FE		Yes
Month FE		Yes
Observations	4,460	4,457
R^2	0.004	0.155

2.5.3 Supply Competition: Margins and Product Complexity over Time

As documented by means of product issuance (see Figure 2.1) and volumes (see Figure 2.9 in the Appendix), the sharp reduction in interest rates during the Great Recession was followed by a distinct shift from Singles to Multis. In light of the experimentally and empirically identified margin difference, the question about possible relations between product prevalence and profitability arises. On the one hand, the parallel rise of both product types during our earlier sample period aligns with both the overall growth in YEPs and our experimentally established impact of interest rate levels on investment propensity; on the other hand, however, the increasing popularity of Multis over the later sample period does not.

Section 2.2.2 provides evidence of the distinctive competitive forces at play in the Swiss YEP issuer market. Carlin (2009) argues that in retail financial markets with imperfectly informed investors, issuers have an incentive to strategically increase product complexity and thereby diminish product comparability. Imperfect comparability shields issuer margins from perfect price competition. In the context of YEPs, Singles are not only less complex than Multis but can also be readily compared based on one-dimensional volatility forecasts. In contrast, Multis require an estimate of every underlying's volatility as well as of their collective correlation structure. Moreover, due to their worst-of payoff function, a Multi's risk-return profile can change substantially by replacing just one underlying asset.

In addition to the prevailing low degree of market concentration, the adoption and steady growth of a multi-issuer platform in 2014 have arguably intensified price competition for standard products. Specifically, for products with common features, the platform allows investors to easily compare price quotes of up to eight issuers, who (not uncommonly) overbid each other's coupons by only a few basis points (see Section 2.2.2 and references therein for details).

To investigate potential complexity effects more systematically, we first regress product margins on a Multi-Dummy and the respective year of issuance. Table 2.8 reports the results. Across all model specifications, i.e., controlling for correlation estimations and issuer fixed effects, we find a significant negative time trend. Margins decrease by approximately 20 basis points per year.

Second, we look at the composition of the growing number of Multis issued over time. Panel (A) of Figure 2.7 indicates that – unsurprisingly – the proportion of non-unique

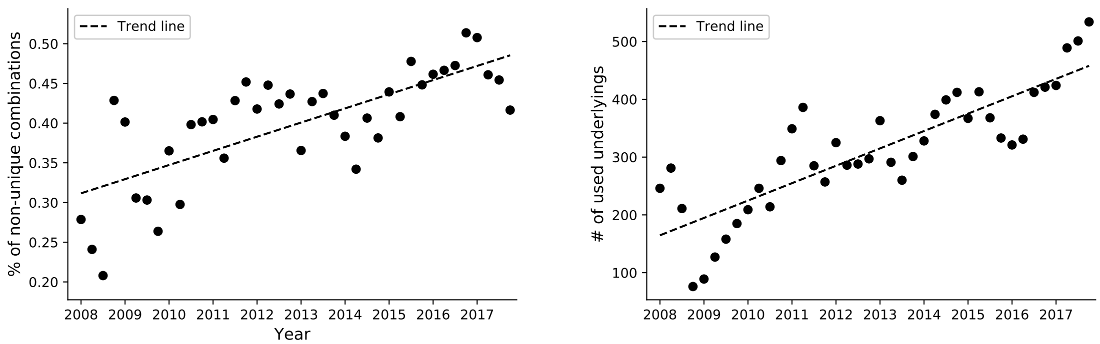
Table 2.8: **Time trend in issuer margins**

Table 2.8 reports coefficient estimates from OLS regressions with issuer margins as dependent variable and a *Multi-Dummy* (equal to one for Multis), the issuance year (*Year*), and the *Risk-free rate (%)* as main regressors of interest. In specifications (1) to (2), Multi margins are based on simple correlation estimations ($Margin_{Hist}$). In specifications (3) to (4) and (5) to (6), Multi margins are based on correlation estimations applying the Ledoit and Wolf (2004) ($Margin_{LW}$) and the Chen et al. (2010) ($Margin_{OAS}$) shrinkage method, respectively (see Section 2.4.1.1 for details). In (1), (3), and (5) raw effects of the Multi-Dummy and issuance year are reported. In (2), (4), and (6) issuer fixed effects are added to the model specifications. The subsample of Singles (Multis) consists of 2,528 (1,932) products. The total sample consists of 4,460 products issued between January 2008 and December 2017. Standard errors are reported in parentheses and are clustered at the issuer and the month level. * , ** , and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Margin_{Hist}		Margin_{LW}		Margin_{OAS}	
	(1)	(2)	(3)	(4)	(5)	(6)
Multi-Dummy	2.220***	2.682***	2.518***	2.997***	2.316***	2.784***
	(0.519)	(0.535)	(0.539)	(0.557)	(0.528)	(0.545)
Year	-0.229***	-0.175***	-0.232***	-0.174***	-0.233***	-0.177***
	(0.063)	(0.041)	(0.067)	(0.043)	(0.065)	(0.042)
Risk-free rate (%)	0.034	-0.138	0.039	-0.141	0.040	-0.137
	(0.294)	(0.247)	(0.305)	(0.255)	(0.298)	(0.248)
Constant	3.275***	2.847***	3.292***	2.836***	3.295***	2.854***
	(0.308)	(0.386)	(0.320)	(0.402)	(0.313)	(0.390)
Issuer FE		Yes		Yes		Yes
Observations	4,460	4,457	4,460	4,457	4,460	4,457
R^2	0.042	0.065	0.050	0.074	0.045	0.068

underlying combinations within a given quarter grows during our sample period. Furthermore, Panel (B) shows that this increasing occurrence of "Multi twins" is counteracted by a continuous (approximately threefold) expansion of the respective underlying universe. The latter trend implies that issuers are inclined to consistently expand the range of available products.

Third, we make use of the steady flow of Multi twins depicted in Panel (A) of Figure 2.7 to test the above conjectured price competition at the individual product level. Crucially, every set of Multi twins comprises, on average, 2.9 different issuers per quarter. Table



(a) **Panel A: Concentration of Multis** (b) **Panel B: Underlyings in use**

Figure 2.7: **Concentration of Multis over time**

Panel A illustrates the percentage of non-unique underlying combinations across all Multis issued during a given quarter between 2008 and 2017. An underlying combination is considered to be non-unique if the same combination of underlying assets is issued multiple times during the same quarter. For every quarter, Panel B shows the number of different underlyings across all issued Multis. The dashed black lines show the respective linear fits (Panel A: $\beta = 0.019$, p-value< 0.01; Panel B: $\beta = 30.07$, p-value< 0.01).

2.9 reports the coefficient estimates of a logistic regression that predicts the likelihood of a (strict) coupon increase based on the number of previously (within the same quarter) issued products with identical underlyings. Across all specifications, i.e., controlling for issuance volume, product characteristics, as well as issuer and quarter fixed effects, and contrary to a decreasing time trend in coupon levels (see above), we find strong evidence that the existence of product twins forces issuers to increase their offered headline rate.

In sum, we interpret these findings as evidence in support of a competition-driven increase in product complexity. Building on well-documented information asymmetries for related products (Egan, 2019), and in conjunction with our own experimental evidence, it appears highly probable that (at least some) retail investors only have incomplete knowledge about BRCs' fair values. Hence, in the face of competition, issuers rationally preserve profits by increasing the complexity of their investment products. Specifically, due to investors' inability to accurately compare sufficiently different products, by switching from issuing Singles to offering more complex and diverse Multis, issuers partially shield their rents against increasing price pressure. This interpretation is further supported by rerunning specification (1) in Table 2.8 but separately interacting the year with a Single and a Multi-Dummy, respectively. While the former coefficient is highly significant (-0.203,

Table 2.9: **Competition for higher margins**

Table 2.9 displays the coefficients of logistic regressions where the dependent variable *Coupon raise* is a dummy equal to one if, in a given quarter, the given product has a higher coupon than the preceding product with the same underlying combination. For all Multis, the first specification regresses *Coupon raise* on *Combination count*, which counts the number of preceding Multis with the same underlying combination issued in the same quarter. The second, third, and four specification control for log *Volume* (mil. CHF) and the main product characteristics, as well as issuer and quarter fixed effects, respectively. Standard errors are reported in parentheses and are clustered at the issuer level. * , ** , and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1) Coupon raise	(2) Coupon raise	(3) Coupon raise	(4) Coupon raise
Combination count	0.017***	0.024***	0.023***	0.024***
	(0.002)	(0.004)	(0.001)	(0.001)
log(Volume)		-0.190***	-0.043	-0.179***
		(0.060)	(0.036)	(0.026)
Maturity (days)		-0.000**	-0.000***	-0.000*
		(0.000)	(0.000)	(0.000)
Barrier level (%)		0.030***	0.033***	0.036***
		(0.004)	(0.002)	(0.003)
Coupon p.a. (%)		0.054***	0.058***	0.073***
		(0.011)	(0.005)	(0.006)
Constant	-1.464***	-0.747	-3.398***	-1.572***
	(0.105)	(0.982)	(0.607)	(0.463)
Issuer FE			Yes	
Quarter FE				Yes
Observations	28,497	17,893	17,893	17,893

p-value < 0.001), the latter only remains marginal significant (-0.270, p-value $= 0.065$), pointing to more sustained competition in the market segment for Singles.

2.5.4 Underlying Combinations and Dependency Bias

In the context of BRCs, the pivotal attribute of any given combination of underlying stocks is their respective correlation. The significance of the embedded dependencies is due to

Multis' worst-of payoff structure: the *lower* the correlation, the *higher* the likelihood of diverging stock performances and, thus, the higher the risk of a barrier event and investment losses. The first-order importance of underlying selection on actual down-side risk calls for a discussion of potentially interacting behavioral phenomena and preferences.

2.5.4.1 Underlying Selection

Our experimental evidence suggests that the presence of multiple underlyings decreases bidding aggressiveness considerably (although not sufficiently to prevent higher margins). A straight-forward approach to manage Multis' amplified down-side risk is by choosing underlyings that are highly correlated.[39] One way of doing so consists of selecting stocks from the same or just a few related industries.

Table 2.15 in the Appendix reports the 30 most frequent underlying assets of Singles and Multis, respectively. Notably, well-known large-cap stocks are frequently used as underlying assets.[40] Figure 2.15 and Figure 2.16 in the Appendix illustrate that (i) Multis' underlying stocks are predominantly from certain industry divisions, (ii) within these divisions, combinations within one or across two industry groups are common, and (iii) underlyings' industry concentration is increasing over time. According to the Standard Industrial Classification (SIC), there exists a total of 416 industry groups (first three digits of SIC code).

In our final sample, the three main industry groups make up 43.3% of all Multis' underlying stocks, i.e., "Computer Programming & Data Processing" (group 737): 21.1%, "Gold and Silver Ores" (group 104): 11.7%, and "Computer & Office Equipment" (group 357): 10.5%. Moreover, in the second half of our sample period, for 52.9% of all Multis with three underlying assets, issuers pick stocks within two or even only one industry group. Across all repeated underlying combinations depicted in Figure 2.7, the following three stock combinations are issued most frequently: Newmont Mining, Barrick Gold, and Goldcorp (all group 104, issued 199 times); Coca-Cola, McDonald's, and Starbucks (group 208 and 581 (2x), issued 179 times); Apple, Alphabet, and Microsoft (group 357 and 737 (2x), issued 152 times).

We also find suggestive evidence that underlying selection is influenced by the (financial) news cycle. For instance, 67% of all repeated underlying combinations are issued in

[39]In the limit, i.e., in the case of perfect correlation, any Multi essentially converges to a Single.

[40]We do not detect any apparent difference in the selection of underlying stocks between Singles and Multis.

just one (respective) quarter.[41] For instance, less than seven months following Twitter's IPO in November 2013, the first Multi on Facebook, Netflix, and Twitter was issued, followed by another 27 such products until December 2017 (end of our sample period). Most recently, on January 20, 2021, Credit Suisse issued a Multi BRC (ISIN CH0575748063) offering a 12% annual coupon on Pfizer, Moderna, and AstraZeneca, i.e., the three leading American and European producers of approved COVID-19 vaccines.

2.5.4.2 Bias in Perceiving Dependencies

When studying the prevalence of seemingly correlated stock combinations, it is key to understand their actual correlation structure and how it determines product returns (margins). Given the importance of underlying dependencies for Multis' overall risk-return profile, this requires an analysis of investors' perception and awareness of *actual* correlation levels. But how do (retail) investors perceive dependencies between stock prices?

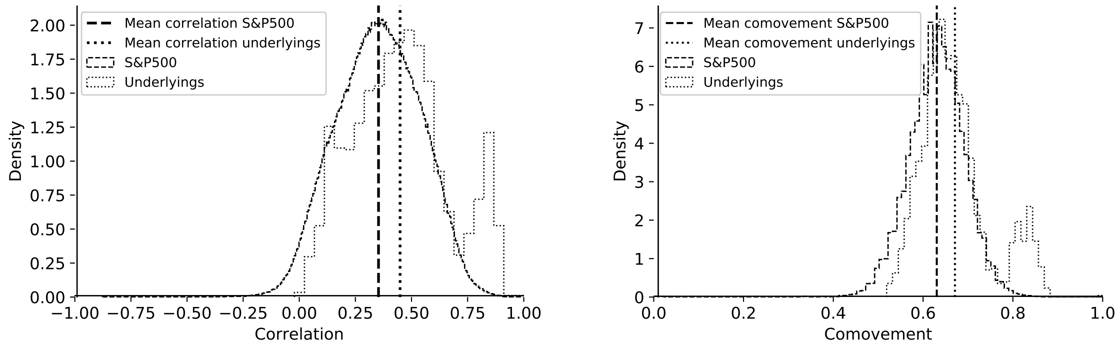
Recent evidence from neuroscience suggests that humans, if confronted with an uncertain environment, generally struggle to identify and adapt to outliers, i.e., the realization of extreme events (d'Acremont and Bossaerts, 2016). Moreover, Ungeheuer and Weber (2020) demonstrate that both experimental participants *and* stock market investors account for the frequency but not the magnitude of return comovement, thereby running the risk of misestimating actual correlations. Building on these findings, we investigate (i) the role of (perceived) dependencies for observed underlying frequencies and (ii) the potential effect of investors' correlation misperception on cross-sectional issuer margins.[42]

Panel A in Figure 2.8 shows the distribution of yearly pairwise correlations of all S&P 500 member stocks over our sample period. For comparison, we plot the correlation distribution for the underlying stock combinations of all Multis in our sample (whereof 62% are S&P 500 members as of year-end 2017).[43] The mean correlation within the S&P 500 universe equals 0.353 and is therefore significantly lower than the 0.449 mean correlation of underlying stocks (p-value < 0.01). Similarly, Panel B in Figure 2.8 shows the corresponding comovement frequency distributions. Following Ungeheuer and Weber (2020),

[41] See Table 2.22 and Table 2.23 in the Internet Appendix for summary statistics.

[42] While we deliberately abstracted from modeling tail risks when pricing BRCs' short option component, thereby accepting conservative estimates of issuer margins, we can now non-parametrically study the consequences of leptokurtic return distributions on the popularity of underlying stock combinations (and associated margins).

[43] Consistent with Multis' worst-of payoff structure, we consider all underlying combinations embedded in a given product. E.g., for a Multi with three underlying assets, we include all three pairwise combinations of underlying stocks.



(a) **Panel A: Correlation distribution** (b) **Panel B: Comovement distribution**

Figure 2.8: **Correlation and comovement – S&P 500 vs. Multi underlyings**

Panel A shows the distributions of annual correlations for both S&P 500 member stocks and between the underlying stocks within each Multi in our final sample. Panel B shows the corresponding distributions of comovement frequencies, which, for any pair of stocks, equals the proportion of days (over one year) with the same sign (direction) of returns. For S&P 500 member stocks, computations are based on calendar years, whereas, for Multi underlyings, computations are based on the twelve months prior to issuance. Both correlations and comovement frequencies are based on daily log returns. The sample period ranges from January 2008 to December 2017. S&P 500 members are selected in accordance with the index composition as of year-end 2017.

the comovement frequency between a given pair of stocks simply equals the proportion of trading days over the past year for which both stocks exhibited the same sign of returns (either both negative or both positive). Hence, the comovement frequency is a simple counting measure based on direction rather than magnitude. Similar to linear correlations, the average comovement within the S&P 500 (0.630) is significantly lower than the average comovement of underlying stocks (0.670, p-value < 0.01).

From Figure 2.8, it becomes evident that investors indeed seem to exhibit a strong preference for highly dependent underlyings. This corroborates our interpretation of the descriptive statistics and anecdotal evidence in Section 2.5.4.1. But what about our hypothesis that investors perceive dependency based on comovement frequency rather than actual linear correlation? Obviously, given their distinct shape and domain, the differences in distributions between Panel A and Panel B in Figure 2.8 cannot be compared directly. To this end, we assign both correlation and comovement ranks to each underlying combination relative to the S&P 500 universe. Specifically, we first compute the percentiles for the distribution of yearly S&P 500 member correlation (comovement) pairs. For instance, the first comovement percentile equals 0.481, and the 99th comovement percentile amounts to 0.772. Second, we map the correlation (comovement) estimate of each underlying combination into the corresponding S&P 500 percentile, which then determines its rank within the S&P 500 benchmark.

Across all combinations of underlying stocks, the average correlation rank is 62.3, whereas the average comovement rank is 64.0. While, on average, Multis' underlying correlations are clearly above those of randomly picked S&P 500 stocks, their comovement ranking appears even higher (p-value = 0.049 for relative ranking difference, Wilcoxon signed-rank test). Splitting our sample into an "early" (2008-12) and "late" (2013-17) period, i.e., controlling for the financial crisis, subperiod-specific rankings reveal that the relative comovement of underlying stocks increased substantially more (+9) than their relative correlation (+5).[44] Overall, these findings suggest that investors' preferences for certain underlying combinations could – at least partially – be driven by a tendency to overestimate actual dependency levels.

In a last step, we investigate the cross-sectional pricing implications of the above dependency measures. To prevent confounding effects of varying payoff contingencies, we again focus on the representative Multi-type with three underlying stocks (see Table 2.5). As before, we control for all other product specifications, the main characteristics of underlying assets, as well as time trends and issuer effects. Moreover, we also account for issuance volumes across Multis.[45] Table 2.10 reports the results. Unsurprisingly, in isolation, both correlation and comovement-based (not shown) dependency measures exhibit a significant negative relation with issuer margins. Taken together, the significant effect of products' (average) underlying correlation vanishes. This indicates that an increase in perceived dependence reduces the margins paid by investors.

Most interestingly, according to the final two model specifications in Table 2.10, the greater the ranking difference between a product's (average) underlying comovement and correlation, the higher its margin. In other words, in the cross section, underlying combinations whose pairwise dependencies are likely to be overestimated by investors offer significantly higher margins to issuers. Moreover, when controlling for potential dependency overestimation (ceteris paribus more likely for low dependencies), the negative effect of average comovement on margins intensifies substantially. Thus, our findings suggest that, while issuers do not sufficiently adjust Multis' coupons to compensate for their embedded

[44] As expected, general dependency levels between stock prices were significantly higher during the crisis.

[45] We obtain qualitatively identical results for our unrestricted sample of Multis with three underlying stocks, i.e., without the constraint of existing data on issuance volume.

Table 2.10: **Issuer margins and dependency measures**

Table 2.10 reports coefficient estimates from OLS regressions with issuer margins of Multis with three underlying assets as dependent variable. For each product, *Avg correlation* denotes the average correlation (based on historical daily log returns) across all three correlation pairs. Similarly, *Avg comovement* denotes the average comovement frequency across all three correlation pairs. Both measures are reported in percent (i.e., scaled by 100) and are based on the twelve months preceding issuance. For each product, *Rank difference* denotes its comovement rank minus its correlation rank, where both ranks are computed relatively to S&P 500 member stocks. *Controls* include a constant, product characteristics, i.e., coupon p.a. (%), maturity (days), barrier level (%), underlyings' average implied volatility (%) and dividend yield (%), issued volume, as well as the prevailing risk-free rate (%) at issuance, see Table 2.16 for details. Standard errors are reported in parentheses and are clustered at the issuer and the month level. * , ** , and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1) Margin	(2) Margin	(3) Margin	(4) Margin	(5) Margin	(6) Margin
Avg correlation	-0.075***	-0.082***	-0.021	-0.024	0.039*	0.032
	(0.005)	(0.006)	(0.012)	(0.017)	(0.019)	(0.031)
Avg comovement			-0.166***	-0.171***	-0.323***	-0.313***
			(0.045)	(0.059)	(0.060)	(0.092)
Rank difference					0.034***	0.030**
					(0.008)	(0.012)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE		Yes		Yes		Yes
Observations	948	939	948	939	948	939
R^2	0.801	0.836	0.811	0.844	0.815	0.847

correlation structure, this discrepancy (margin) is (i) decreasing in the perceived dependency level of underlying stocks, but (ii) increasing in the dependency overestimation by investors.

2.6 Conclusion

Studying the market for yield enhancement products (YEPs) in Switzerland between 2008 and 2017, we document a substantial increase in market size, followed by a distinct rise in product complexity. This pattern is paralleled by firstly falling and then plateauing low interest rates. Via the means of laboratory control, we show that, while decreasing interest rates increase individuals' overall willingness to bear risk, it is their misestimation of correlation effects that creates demand for more complex products. By analyzing 4,460 issued YEPs, we find that (i) estimated issuer margins are increasing in product complexity, (ii) average investment returns are negative, (iii) increasing product complexity appears driven by issuer competition and to cater to investors' bias in the perception of stock price dependencies.

In the face of high economic uncertainty as well as surging private and public debt levels, interest rates are expected to remain low in most advanced economies for the foreseeable future, a phenomenon aptly termed "low for long." While the debate about the risk-taking consequences of such unconventional monetary policies is continuing (see, e.g., Rajan (2013) for an optimistic and Stein (2013) for a more conservative outlook), seminal finance theories, e.g., on portfolio choice (Campbell and Sigalov, 2020), are currently being revised to account for reaching for yield behavior. Moreover, as shown by Bordalo et al. (2016) and Lian et al. (2019), this environment also offers new opportunities for financial innovation.

As recent as November 2019, structured investment products received approval of the Swiss pension supervisory authority (OPSC).[46] Considering the growing yield-generating pressure experienced by pension funds globally, educating the broader investor community about the *complete* risk-return profile of emerging or newly accredited investment alternatives is all the more of high policy relevance. To assist ongoing regulation, a better understanding of both demand and supply driven mechanisms is crucial for shedding light on the effect of low interest regimes on investment decisions, and, thus, on financial stability. This paper takes a step in this direction.

[46] For details, see the Swiss Structured Products Association (SSPA) media release available via https://www.svsp-verband.ch/en/media-release/2019/.

A.2 Pricing Formula

At issuance $t = 0$, the value of a Single (BRC with one underlying asset) can be calculated via the following closed-form solution:

$$v_{Single} = N \times e^{(c-r)T} - \frac{N}{S_0} \times p_{di},$$

where N is the nominal value of the Single, c the coupon p.a., r the risk-free rate p.a. at issuance, T the product maturity (in years), S_0 the value of the underlying asset at issuance, and p_{di} the value of a European down-and-in put option on the underlying asset (at issuance). Here, both c and r are expressed using continuous compounding.

Under the assumptions of Black and Scholes (1973), the risk-neutral dynamics of the underlying asset with continuous (dividend) yield μ are:

$$dS_t = (r - \mu)S_t dt + \sigma S_t dW_t,$$

where S_t denotes the underlying asset price at time t, σ the volatility of the underlying asset, and $\{W_t, t \geq 0\}$ a Brownian motion.

At $t = 0$, the value of the embedded European down-and-in put option then equals (see, e.g., Jeanblanc, Yor, and Chesney, 2009):

$$\begin{aligned} p_{di} = &- S_0 N(-x_1) e^{-\mu T} + K e^{-rT} N(-x_1 + \sigma\sqrt{T}) + S_0 e^{-\mu T} \left(\frac{H}{S_0}\right)^{2\lambda} [N(y) - N(y_1)] \\ &- K e^{-rT} \left(\frac{H}{S_0}\right)^{2\lambda - 2} \left[N(y - \sigma\sqrt{T}) - N(y_1 - \sigma\sqrt{T})\right], \end{aligned}$$

where H denotes the put option's barrier and:

$$\lambda = \frac{r - \mu + \frac{\sigma^2}{2}}{\sigma^2} \qquad x_1 = \frac{\ln(S_0/H)}{\sigma\sqrt{T}} + \lambda\sigma\sqrt{T}$$

$$y = \frac{\ln(H^2/(S_0 K))}{\sigma\sqrt{T}} + \lambda\sigma\sqrt{T} \qquad y_1 = \frac{\ln(H/S_0)}{\sigma\sqrt{T}} + \lambda\sigma\sqrt{T}.$$

B.2 Additional Tables and Figures

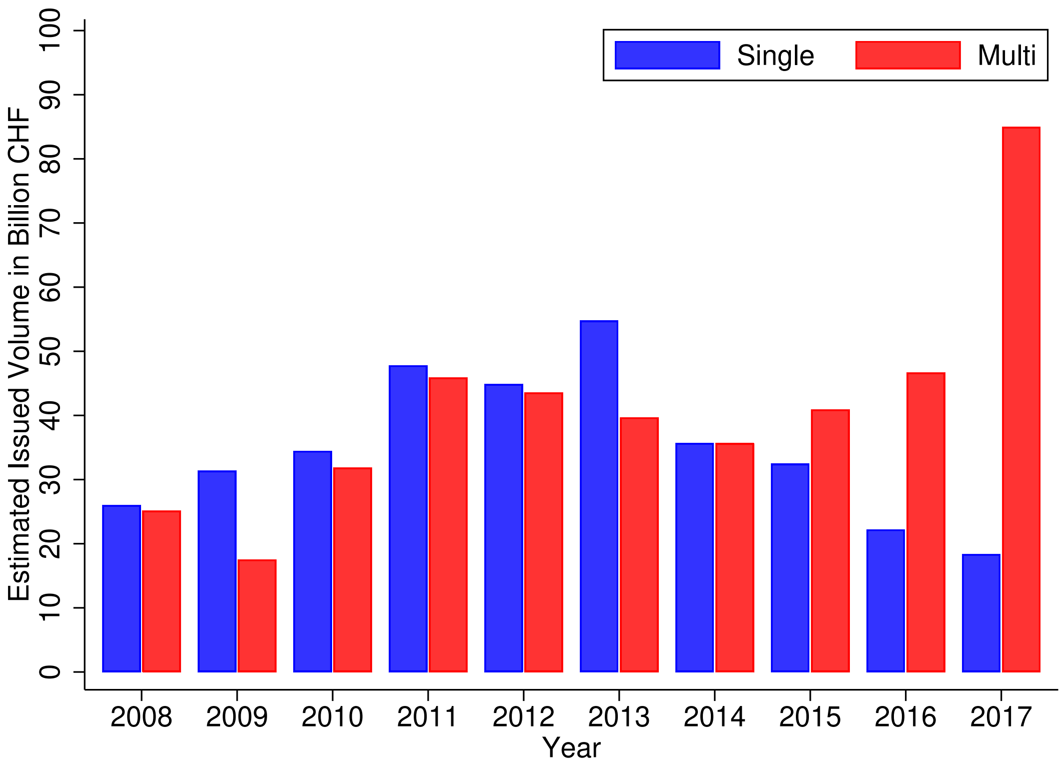
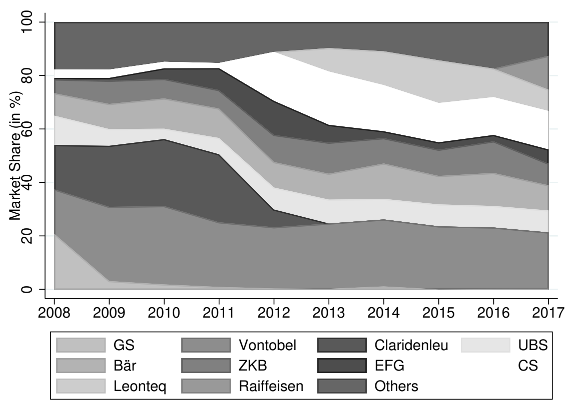
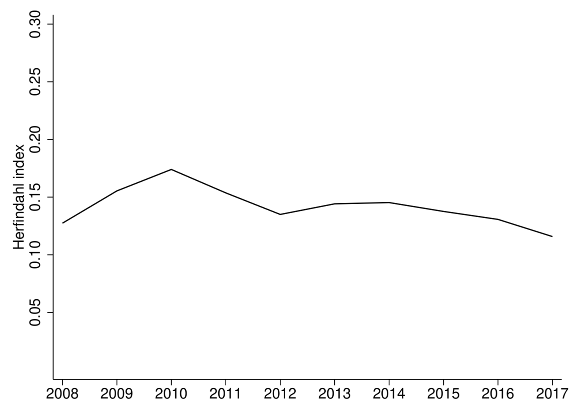


Figure 2.9: **BRCs estimated issuance volume**

Figure 2.9 shows the evolution of estimated BRC issuance volume between January 2008 and December 2017. We classify BRCs as "Singles" (one underlying asset) or "Multis" (more than one underlying asset), respectively. In total, we have volume data for 28,960 BRCs: 11,067 Singles and 17,893 Multis. Estimates of issuance volumes are calculated by multiplying annual mean volumes by the respective number of issued products. Volume observations are winsorized at the 5^{th} and 95^{th} percentile.



(a) **Panel A: Market shares**



(b) **Panel B: Herfindahl index**

Figure 2.10: **Competition in the market for YEP**

Panel A in Figure 2.10 illustrates the respective market share (turnover) of the largest YEP issuers in Switzerland between 2008 and 2017. Panel B plots the evolution of the corresponding Herfindahl index across all YEP issuers. Source: Market Report Express provided by SIX Structured Products (SIX Securities & Exchanges).

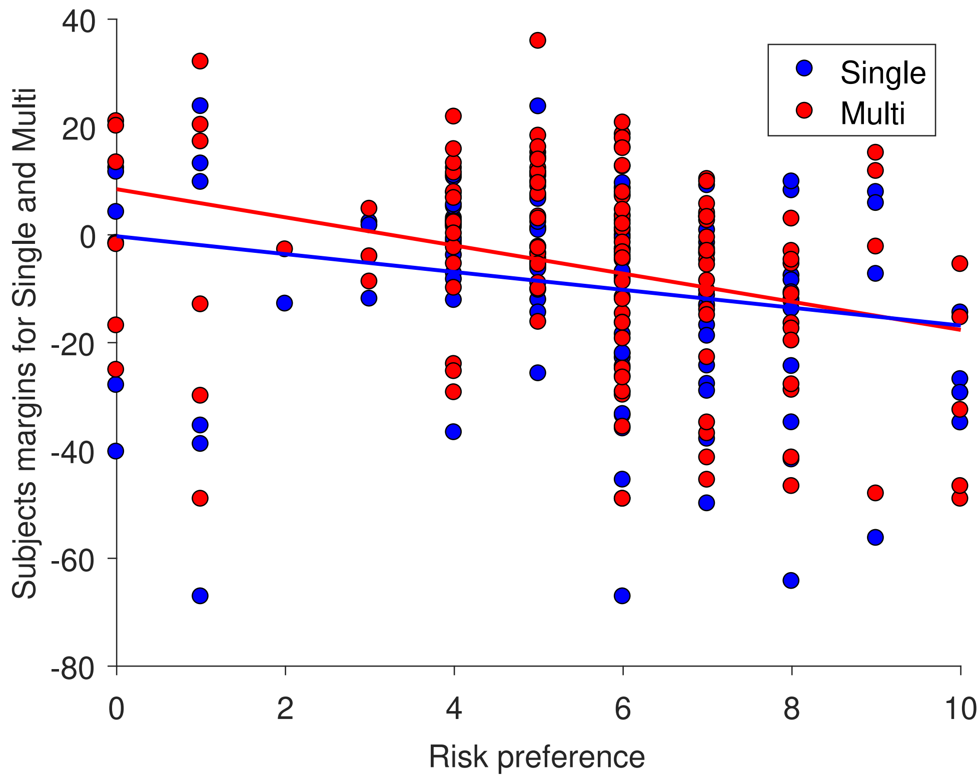


Figure 2.11: **Margins and risk preferences**

Figure 2.11 shows the relation between participants' risk preferences and their average implied margin for Singles (blue) and Multis (red). Risk preferences are measured as participants' switching point in the Holt and Laury (2002) elicitation task. The blue line shows the linear fit for Singles ($\beta = -1.66$, p-value $= 0.02$) and the red line for Multis ($\beta = -2.61$, p-value < 0.01), respectively.

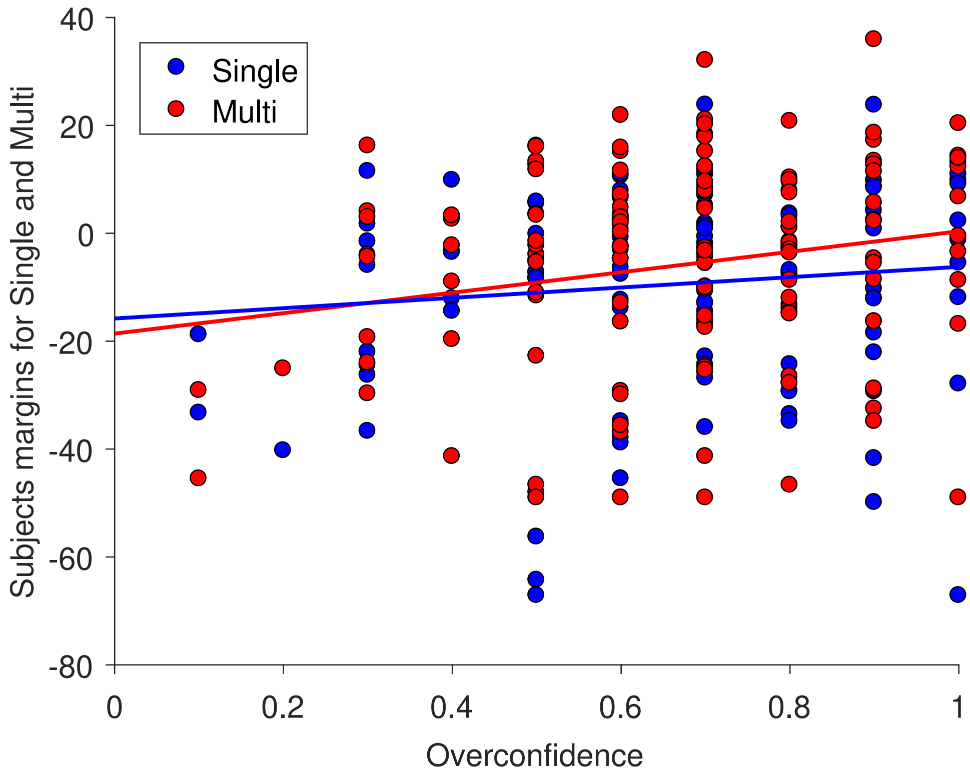


Figure 2.12: **Margins and overconfidence**

Figure 2.12 shows the relation between participants' overconfidence and their average implied margin for Singles (blue) and Multis (red). Overconfidence is measured as proportion of incorrect intervals in the Alpert and Raiffa (1982) interval production task: participants are confronted with ten knowledge questions, for each of which they have to provide 90% confidence intervals. A value of one indicates that a given participant's intervals did *not* contain the true answer to any of the ten questions. The blue line shows the linear fit for Singles ($\beta = 9.58$, p-value $= 0.24$) and the red line for Multis ($\beta = 18.95$, p-value $= 0.02$).

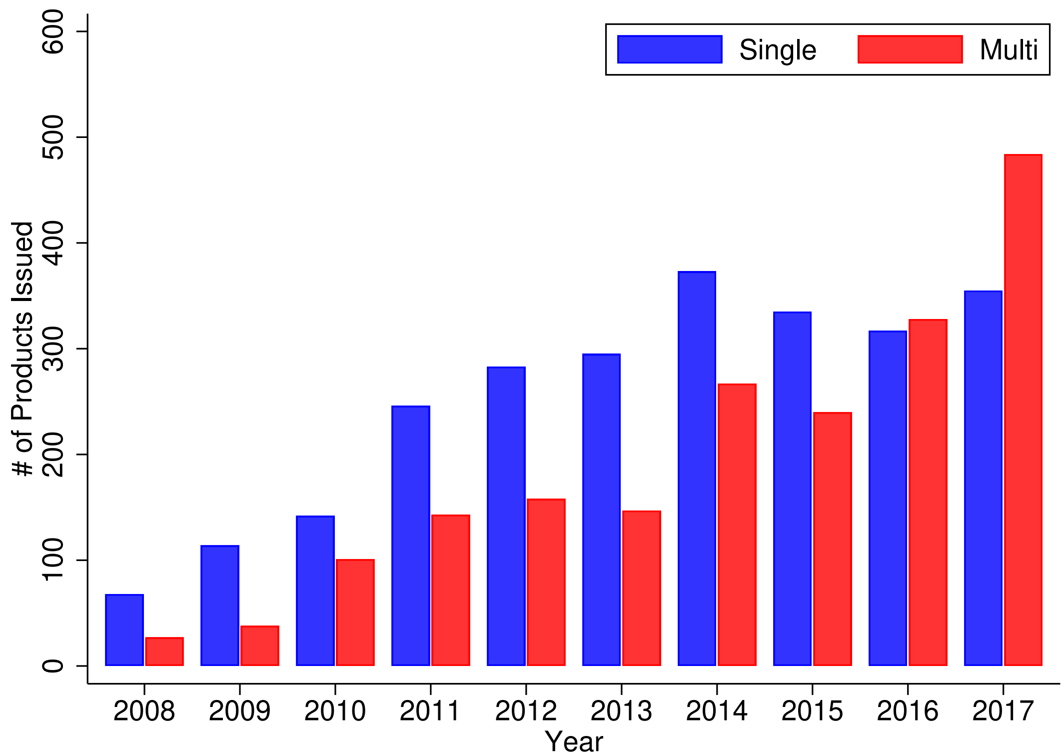


Figure 2.13: **BRCs issuance over time – final sample**

Figure 2.13 shows the evolution of BRC issued between January 2008 and December 2017 in our final sample. We classify BRCs as "Singles" (one underlying asset) or "Multis" (more than one underlying asset), respectively. In total, the final sample consists of 4,460 issued BRCs: 2,528 Singles and 1,932 Multis.

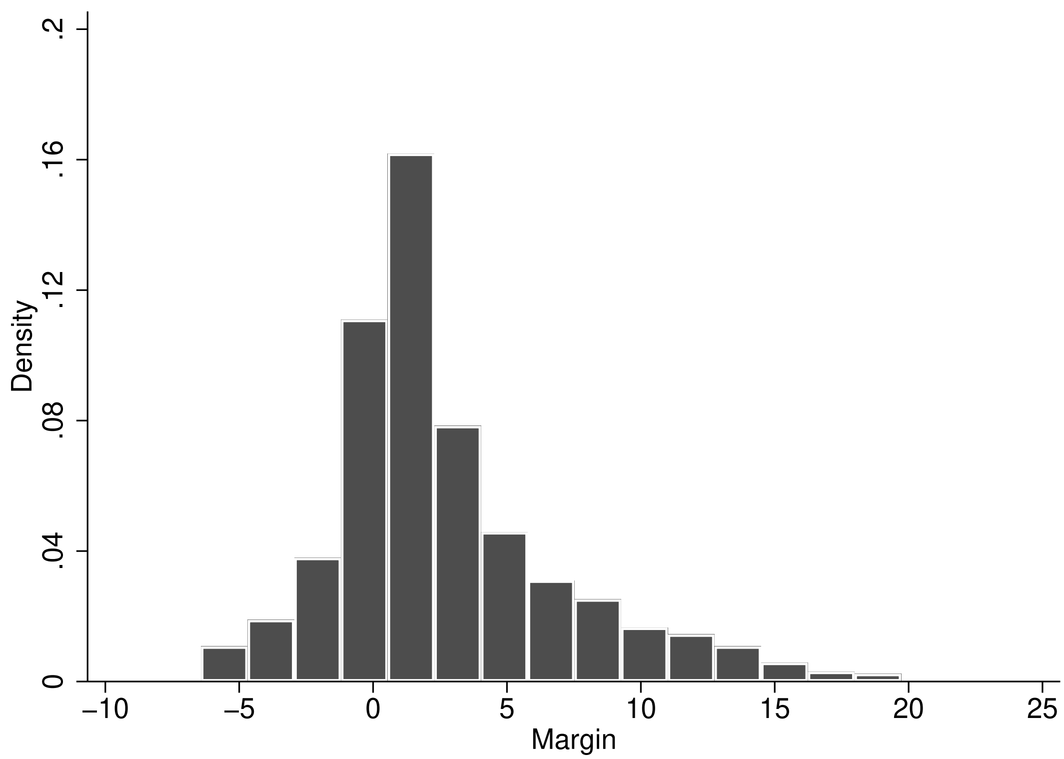


Figure 2.14: **Issuer margins**

Figure 2.14 shows the distribution of estimated margins (in %) earned by BRC issuers. Displayed margins are winsorized at one and hundred percent. In total, the final sample consists of 4,460 BRCs issued between January 2008 and December 2017.

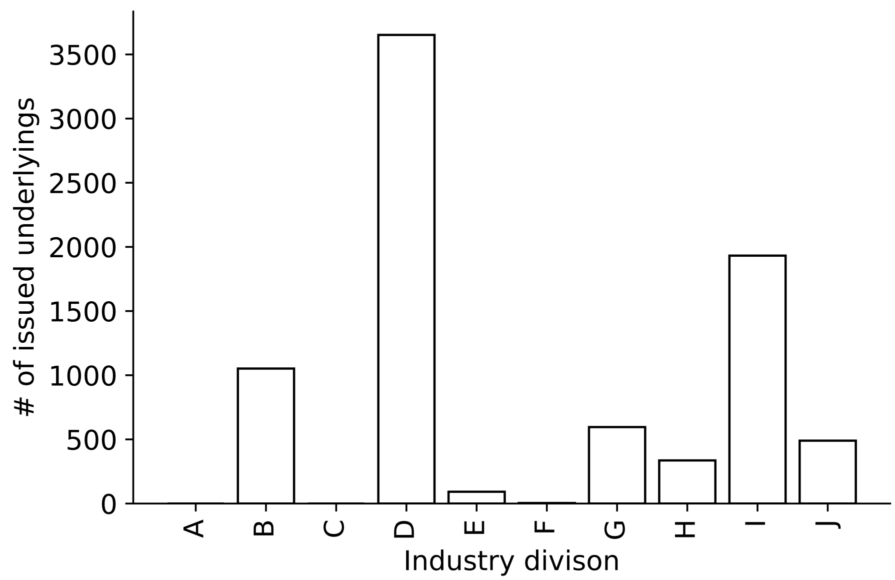


Figure 2.15: **Distribution of underlyings stocks across SIC divisions**

Figure 2.15 shows the distribution of underlying stocks across all BRCs in our final sample, classified by Standard Industrial Classification (SIC) division: A = Agriculture, B = Mining, C = Construction, D = Manufacturing, E = Transportation & Communication, F = Wholesale Trade, G = Retail Trade, H = Finance & Insurance, I = Services, J = Public Administration. In total, the final sample consists of 4,460 issued BRCs: 2,528 Singles and 1,932 Multis.

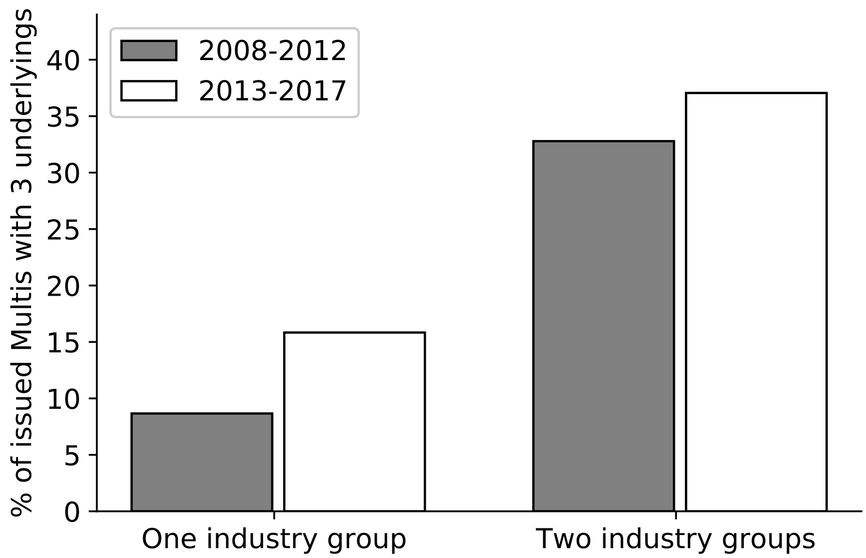


Figure 2.16: **Industry concentration of underlying combinations**

Figure 2.16 shows the percentage of Multis with three underlyings whose underlying stocks are either all from the same industry group or from two industry groups. In total, there exist 416 Standard Industrial Classification (SIC) industry groups. The sample period is split into the first and second five years, respectively. The final sample consists of 1,691 issued Multis with three underlying stocks.

Table 2.11: **Treatment Overview**

Table 2.11 shows an overview of the different experimental treatments. Treatments differ along the interest rate and the volatility dimension. In each treatment, the respective parameter changes in isolation, e.g., the volatility level (moderate vs. high) of the underlying asset(s), or the level of the risk-free interest rate (negative vs. zero vs. positive).

Volatility level	*Interest environment*: Normal (3.00%)	Zero (0.00%)	Negative (-2.00%)
Moderate (13.7%)	Treatment 1	Treatment 2	Treatment 3
High (27.4%)	Treatment 4	Treatment 5	Treatment 6

Table 2.12: **Product parameters overview**

Table 2.12 provides an overview of the products and their parameters used in the different treatments of the experiment. Overall, participants have to evaluate twelve products, half of which are Singles, over six rounds. In any given round, Singles and Multis only differ in the number of underlying stocks. Columns *Coupon S* and *Coupon M* show the values of the coupon payment for each product type. Column *Vola* indicates the volatility level in each round, and column *rf-rate* shows the corresponding risk-free rate. The columns *HitProb S* and *HitProb M* present the actual probabilities of a barrier event for the Single and Multi in each round, respectively.

Round	Coupon S	Coupon M	Vola	rf-rate	HitProb S	HitProb M
1	17.00%	17.00%	13.7%	3.00%	16.94%	30.97%
2	17.00%	17.00%	13.7%	0.00%	16.94%	30.97%
3	17.00%	17.00%	13.7%	-2.00%	16.94%	30.97%
4	17.00%	17.00%	27.4%	3.00%	55.91%	80.62%
5	17.00%	17.00%	27.4%	0.00%	55.91%	80.62%
6	17.00%	17.00%	27.4%	-2.00%	55.91%	80.62%

Table 2.13: **Summary statistics experiment**

Table 2.13 shows summary statistics (mean, standard deviation, first quartile, median, third quartile) for participants' estimates during the main experimental task. WTP_{Single} and WTP_{Multi} indicate participants' willingness-to-pay for Singles and Multis, respectively. $Prob_{Single}$ and $Prob_{Multi}$ denote participants' estimated probabilities of a barrier event for Singles and Multis, respectively. $Misestmation_{Single}$ and $Misestimation_{Multi}$ indicate the difference between the true probability and the respective estimate for Singles and Multis, respectively. The total number of observations is 606.

	Mean	Std	Q1	Median	Q3
WTP$_{Single}$	96.49	18.84	85.00	100.00	110.00
WTP$_{Multi}$	89.52	19.80	73.50	90.75	105.00
Prob$_{Single}$	38.67	22.88	20.00	36.00	50.00
Prob$_{Multi}$	49.61	24.85	30.00	50.00	70.00
Misestimation$_{Single}$	-2.25	29.68	-23.06	-3.06	15.91
Misestimation$_{Multi}$	6.18	34.44	-19.03	5.97	30.62
Observations	606				

Table 2.14: **Issuer margins of Multis with three underlying assets**

Table 2.14 reports coefficient estimates from OLS regressions with issuer margins of Multis with three underlying assets as dependent variable. For each product, *Avg correlation* denotes the average correlation (based on historical daily log returns) across all three correlation pairs. Similarly, *Min. correlation* denotes the smallest correlation across all three correlation pairs. *Controls* include a constant, product characteristics, i.e., coupon p.a. (%), maturity (days), barrier level (%), underlyings' average implied volatility (%) and dividend yield (%), as well as the prevailing risk-free rate (%) at issuance, see Table 2.16 for details. Standard errors are reported in parentheses and are clustered at the issuer and the month level. * , ** , and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1) Margin	(2) Margin	(3) Margin	(4) Margin	(5) Margin	(6) Margin
Avg correlation	-0.032***	-0.084***	-0.089***			
	(0.005)	(0.007)	(0.006)			
Min. correlation				-0.028***	-0.074***	-0.077***
				(0.004)	(0.005)	(0.005)
Controls		Yes	Yes		Yes	Yes
Issuer FE			Yes			Yes
Month FE			Yes			Yes
Observations	1,691	1,691	1,679	1,691	1,691	1,679
R^2	0.010	0.839	0.862	0.009	0.838	0.859

Table 2.15: **Underlying equities**

Table 2.15 reports the 30 most frequently used underlying assets for both Singles and Multis in the final sample, as well as the number of linked products and their respective percentage share in the initial data set. The sample consists of 4,460 BRCs and 172 corresponding underlying assets.

	Single			Multi	
Underlying	Products	% share	Underlying	Products	% share
Microsoft	113	4.47	Microsoft	429	7.61
Caterpillar	108	4.27	Alphabet	365	6.48
General Electric	103	4.07	Coca Cola	272	4.83
Tesla	101	4.00	General Electric	248	4.40
Pfizer	88	3.48	Newmont Mining	221	3.92
Facebook	81	3.20	Goldcorp	211	3.74
Intel	75	2.97	Facebook	205	3.64
Alphabet	63	2.49	McDonalds	200	3.55
Exxon Mobil	55	2.18	Intel	176	3.12
Twitter	53	2.10	Pfizer	174	3.09
Newmont Mining	52	2.06	Starbucks	169	3.00
Cisco	50	1.98	Caterpillar	165	2.93
Alibaba	49	1.94	Netflix	143	2.54
HP	44	1.74	Cisco	88	1.56
Goldcorp	42	1.66	Nike	87	1.54
Starbucks	42	1.66	IBM	78	1.38
IBM	41	1.62	Gilead Sciences	74	1.31
Coca Cola	35	1.38	Johnson & Johnson	63	1.12
McDonalds	34	1.35	Exxon Mobil	61	1.08
Netflix	34	1.35	Mondelez	61	1.08
Gilead Sciences	29	1.15	Celgene	52	0.92
United States Steel	28	1.11	Biogen	50	0.89
Johnson & Johnson	26	1.03	Tesla	50	0.89
Halliburton	26	1.03	Disney Walt	48	0.85
Nike	24	0.95	Twitter	47	0.83
Petroleo Brasileiro	22	0.87	Procter & Gamble	46	0.82
JP Morgan	21	0.83	Visa	45	0.80
Celgene	21	0.83	Nvidia	35	0.62
GoPro	21	0.83	Alibaba	34	0.60
Penney JC	20	0.79	Walt Mart Stores	32	0.57

Table 2.16: **Variable definitions**

Variable name	Description	Source
Year	Calendar year of product issuance date	Data set
Issuer	Product issuer	Data set
Nominal value, N	Value invested in product at issuance (excluding fees)	Data set
Coupon p.a., c	Annual coupon of product (in %)	Data set
Maturity, T	Life time of product (in days)	Data set
Barrier level, H	Barrier level of product's embedded put option	Data set
Strike price, S_0	Strike price of embedded option, equal to the value of underlying asset at issuance	Data set
Risk-free rate, r	OIS rate linearly interpolated from two nearest maturities	Bloomberg
Dividend yield, μ	Dividend yield of underlying asset over past 12 months	CRSP
Implied volatility, σ	Implied volatility bi-linearly interpolated from four closest options with respect to strike price and maturity	OptionMetrics Ivy DB US
Volume	Issuance volume (in CHF) winsorized at 5% and 95%	Bloomberg
Correlation	Linear correlation between log returns of two underlying assets over past 12 months (see Section 2.4.1.1 for different estimation approaches)	CRSP
Comovement	Relative frequency that two underlyings assets have same sign of daily returns over past 12 months	CRSP
Margin	Estimated issuer margin (see Section 2.5.1)	Pricing model
Product return	Realized investment return (see Section 2.5.2)	Own calculations
Misestimation	Difference between true probability of barrier event and participant's estimate thereof	Experiment
Invest Decision	Participants' conditional willingness to invest	Experiment
WTP	Participant's willingness-to-pay for a product	Experiment
Multi-Dummy	Equal to one (zero) for Multis (Singles)	Experiment
Interest-Dummy	Equal to one (zero) in positive (non-positive) interest rate treatments	Experiment
Vola-Dummy	Equal to one (zero) in high (moderate) volatility treatments	Experiment
Female/Male	Participant's gender	Experiment
Age	Participant's age	Experiment
Risk preferences	Participant's risk preferences measured as their switching point in Holt and Laury (2002)	Experiment
Overconfidence	Participant's normalized judgmental overconfidence measured following Alpert and Raiffa (1982)	Experiment

C.2 Internet Appendix

This Internet Appendix provides additional analyses and results that were omitted from our paper "Low Interest Rates, Bounded Rationality, and Product Complexity: Demand and Supply Effects for Retail Financial Markets." The discussion thereof can be found in the main text of the paper. In addition, the instructions of the experiment are attached at the end.

Table 2.17: **Participant characteristics**

Table 2.17 provides an overview of participant characteristics in the experiment. *Age* is reported in years. *Male* denotes a dummy variable that equals one if a participant reveals to be male. *Familiar with SP* is a dummy variable that equals one if a participant indicates to be familiar with structured products. *Risk preferences* indicates participants' risk preferences measured as their switching point in the Holt and Laury (2002) elicitation task. *Confidence measure* indicates participants' normalized overconfidence measured as the proportion of incorrect intervals in the Alpert and Raiffa (1982) interval production task. The average participant is 23 years old, slightly risk-averse, and significantly overconfident. Slightly more than half of all participants are female and approximately one third considers themselves to be familiar with structured products. The total number of participants is 125.

	Mean	Std	Min	Max
Age	23.77	4.24	20	62
Male	45.6%	-	-	-
Familiar with SP	32.8%	-	-	-
Risk preferences	5.51	2.30	0.00	10.00
Confidence measure	0.67	0.20	0.10	1.00
Observations	125			

Table 2.18: **Summary statistics of all barrier reverse convertibles in data set**

Table 2.18 reports summary statistics of product characteristics for all barrier reverse convertibles in our initial data set. *Coupon p.a.* (%) is the product's annual coupon rate (extracted from its payoff description). *Barrier level* (%) is the barrier level of the product's embedded put option in percentage of underlying values at fixing. *Maturity* (days) is the product's time to maturity at issuance. *# of underlyings* indicates the number of payoff-relevant underlying asset(s). *Volume (mil. CHF)* is the issued volume. Bloomberg provides data on issued volumes for 28,960 products of our initial data set.

	Mean	Std	Min	Q1	Median	Q3	Max
Coupon p.a. (%)	8.70	3.67	0.20	6.15	8.00	10.26	57.34
Barrier level (%)	67.19	9.35	30.00	60.00	69.00	75.00	93.00
Maturity (days)	392	177	60	357	359	386	1,821
# of underlyings	2.25	1.07	1	1	3	3	14
Volume (mil. CHF)	17.03	10.55	2.00	10.00	10.00	30.00	40.00
Observations	47,080						

Table 2.19: **Overview of barrier reverse convertibles in final sample**

Table 2.19 presents the number of issued Singles and Multis in our final data set grouped by issuer (Panel A) and year (Panel B). The subsample of Singles (Multis) consists of 2,528 (1,932) products. The total sample consists of 4,460 products issued between January 2008 and December 2017.

Panel A: By issuer

	Single	Multi
Vontobel	1,282	493
Julius Bär	659	217
EFG	158	137
Leonteq	133	312
CLEU	80	75
Credit Suisse	64	332
ZKB	31	88
HSBC	25	1
UBS	22	99
J.P. Morgan	18	20

Panel B: By year

	Single	Multi
Issued in 2008	68	27
2009	114	38
2010	142	101
2011	246	143
2012	283	158
2013	295	147
2014	373	267
2015	335	240
2016	317	328
2017	355	483

Table 2.20: **Closed-form vs. Monte Carlo pricing of Singles**

Table 2.20 reports summary statistics of Single price estimates from the closed-form solution in the Black and Scholes (1973) model and a standard Monte Carlo method, respectively. The results of the Monte Carlo procedure are based on 365 time steps (within one year) and 50,000 price path simulations per underlying asset. $Margin_{closed}$ denotes the margins implied by the closed-form solution. $Margin_{sim}$ denotes the margins implied by the Monte Carlo method. The small differences between the two are caused by a slightly lower barrier event probability, i.e., a lower activation risk of the embedded barrier put option, implied by the latter's discretization error.

	Mean	Std	p2.5	Q1	Median	Q3	p97.5
Margin$_{closed}$	2.10	4.51	-1.767	1.047	1.449	3.158	8.921
Margin$_{sim}$	2.01	4.49	-1.844	0.972	1.377	3.081	8.769
Observations	2,528						

Table 2.21: **Issuer margins – Singles vs. Multis II**

Table 2.21, reports coefficient estimates from OLS regressions with issuer margins as dependent variable and a *Multi-Dummy* (equal to one for Multis) as main regressor of interest. In specifications (1) to (2), Multi margins are based on simple correlation estimations ($Margin_{Hist}$). In specifications (3) to (4), and (5) to (6), Multi margins are based on correlation estimations applying the Ledoit and Wolf (2004) ($Margin_{LW}$) and the Chen et al. (2010) ($Margin_{OAS}$) shrinkage method, respectively (see Section 2.4.1.1 for details). In (1), (3), and (5), the effects of a *Multi-Dummy*, product characteristics (including valuation inputs), and the *Risk-free rate (%)* are reported. In (2), (4), and (6), issuer and month fixed effects are added to the model specifications. The subsample of Singles (Multis) consists of 2,528 (1,932) products. The total sample consists of 4,460 products issued between January 2008 and December 2017. Standard errors are reported in parentheses and are clustered at the issuer and the month level. * , ** , and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Margin_{Hist}		Margin_{LW}		Margin_{OAS}	
	(1)	(2)	(3)	(4)	(5)	(6)
Multi-Dummy	6.505***	6.687***	6.849***	7.054***	6.602***	6.801***
	(0.270)	(0.344)	(0.277)	(0.357)	(0.267)	(0.349)
Coupon p.a. (%)	-0.918***	-0.932***	-0.920***	-0.935***	-0.916***	-0.931***
	(0.045)	(0.049)	(0.046)	(0.050)	(0.045)	(0.049)
Barrier level (%)	0.410***	0.402***	0.417***	0.409***	0.412***	0.403***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Maturity (in days)	0.007***	0.007***	0.008***	0.008***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Divid. yield (%)	0.283***	0.292***	0.268***	0.276***	0.267***	0.275***
	(0.044)	(0.041)	(0.058)	(0.057)	(0.058)	(0.057)
Implied vola. (%)	0.580***	0.583***	0.589***	0.592***	0.582***	0.585***
	(0.026)	(0.026)	(0.027)	(0.027)	(0.026)	(0.026)
Risk-free rate (%)	1.241***	-0.962	1.263***	-1.129	1.246***	-1.113
	(0.200)	(1.624)	(0.197)	(1.632)	(0.194)	(1.596)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Issuer FE		Yes		Yes		Yes
Month FE		Yes		Yes		Yes
Observations	4,460	4,457	4,460	4,457	4,460	4,457
R^2	0.659	0.682	0.653	0.676	0.652	0.674

Table 2.22: **Product characteristics – same underlyings and issuance quarter**

Table 2.22 reports the summary statistics of the *average* characteristics of non-unique products (i.e., identical underlying combinations) issued in the same quarter of any given year. *Coupon p.a.* (%) is the products' mean annual coupon rate. *Barrier level* (%) is the mean barrier level of the products' embedded put option in percentage of underlying values at fixing. *Maturity* (days) is the products' mean time to maturity at issuance. In total, there are 3,870 sets of non-unique products issued in different quarters.

	Mean	Std	Min	Q1	Median	Q3	Max
Coupon p.a. (%)	9.47	1.94	7.62	8.56	9.39	10.29	11.63
Barrier level (%)	63.75	4.80	58.78	61.76	64.00	65.95	68.17
Maturity (days)	396.24	92.55	315.84	356.38	387.88	428.90	501.60
Observations	3,870						

Table 2.23: **Product characteristics – same underlyings**

Table 2.23 reports the summary statistics of the *average* characteristics of non-unique products (i.e., identical underlying combinations). *Coupon p.a.* (%) is the products' mean annual coupon rate. *Barrier level* (%) is the mean barrier level of the products' embedded put option in percentage of underlying values at fixing. *Maturity* (days) is the products' mean time to maturity at issuance. In total, there are 2,949 sets of non-unique products issued across our sample period.

	Mean	Std	Min	Q1	Median	Q3	Max
Coupon p.a. (%)	9.55	1.99	7.50	8.55	9.42	10.43	12.09
Barrier level (%)	63.60	4.79	58.01	61.48	63.89	65.92	68.44
Maturity (days)	392.32	95.01	302.55	350.81	383.64	426.16	515.78
Observations	2,949						

Experimental Instructions

The complete set of instructions (including comprehension questions) for our laboratory experiment follows on the next four pages.

Welcome to the Finance-Lab!

Please read the following instructions carefully. Fully understanding the instructions will increase your chances of achieving a higher number of bonus points for the final exam of the lecture "Environmental and Financial Sustainability". At the end of these instructions, you will find 3 control questions. We will also go through a short training session before starting the experiment. However, please take the time to understand the instructions fully. If you have any questions, please raise your hand and an experimenter will come over to help.

Task

In this experiment, you will have the opportunity to buy different financial products. Your goal is to maximize your total wealth. The experiment consists of 12 independent rounds. Each round is divided into two stages.

At the beginning of **each round,** you will be provided with an initial amount of 140 ECU (experimental currency units). During every round, you will have the opportunity to use your cash to buy **one** financial product or to invest your money at the risk-free rate. The price of the product is not yet fixed. It will be determined by chance. You will never have to spend more for a product than you are willing to. You may even be able to buy it for less. Here is how it works:

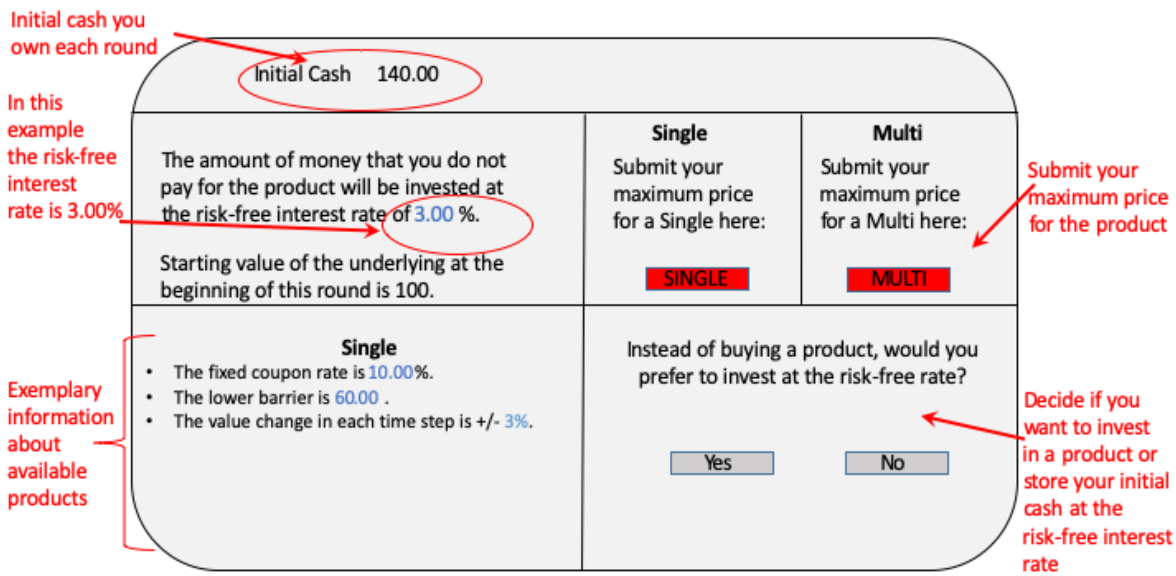
Stage 1

At the first stage of each round, all participants receive the same public information about all products available for purchase. This information will help you to determine the value of each product. To do this more easily, you will first be asked to estimate each product's value components. Then, for a given list of different prices, you have to decide whether you want to buy the product or not. This procedure is carried out for all products. In summary, it should help you to make better decisions.

After all participants have made their decisions, the computer **randomly** selects one product. Thereafter, the computer **randomly** sets the price for the selected product. If this random price is less than or equal to your willingness to pay for the selected product, you will purchase the product at that randomly determined price. In this case, the randomly determined price gets deducted from your initial cash amount and the remainder is automatically invested at the risk-free rate. In contrast, if the random price is higher than your willingness to pay for the selected product, your entire initial cash amount is invested at the risk-free rate. However, if you prefer to invest your initial cash amount at the risk-free rate, independently of the randomly determined price, you will always have the chance to do so. Notice, the **risk-free rate can change** between rounds.

For example, if you are willing to buy the selected product for up to 110 ECU and the randomly determined price turns out to be 105 ECU, you only have to pay 105 ECU in return for the product. The remaining 35 ECU (=140-105) will automatically be invested at the current risk-free rate. If, however, the randomly determined price turns out to be higher than 110 ECU, you will not acquire the product and your total initial cash amount is automatically invested at the current risk-free rate.

Example screen of stage 1:

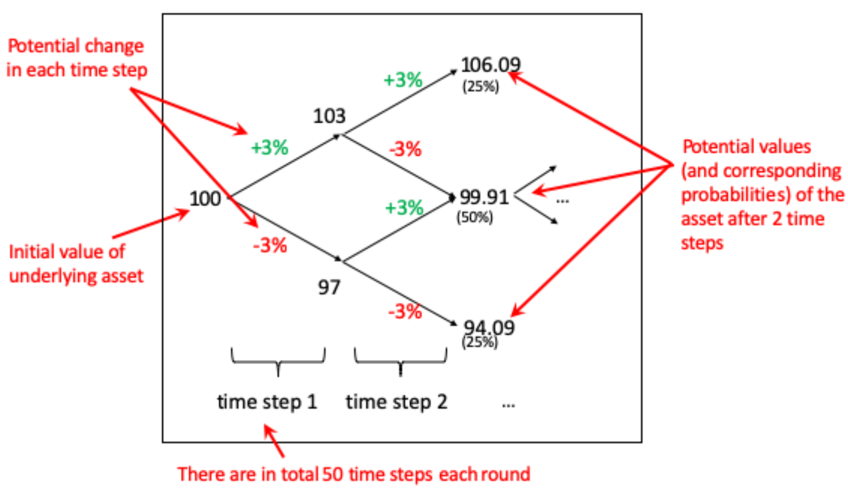


Stage 2

At the second stage of each round, your total wealth of that round is displayed. Additionally, if you have previously purchased a product at stage 1, the screen shows this product's final payoff. In this case, your total wealth corresponds to the sum of your remaining cash account and the product's payoff. Your goal should be to maximize your total wealth in every period. Now, we finally turn to the available products themselves.

Financial products

It is important to understand that the payoffs of the financial products depend on the development of underlying assets. Every asset starts at a nominal value of 100 ECU. Between stage 1 and stage 2, each asset then changes its value 50 times. In particular, for a total of 50 time steps, the computer randomly determines whether the asset value either increases or decreases. At every time step, an increase or a decrease in asset value is equally likely, that means both can happen with a probability of 50%. For example, if the asset's value changes correspond to ±3%, then, at each time step, the asset either moves up by +3% or down by -3%, each with a probability of 50%.



83

Universität Zürich[UZH]

Department of Banking and Finance
Plattenstrasse 32
www.bf.uzh.ch

There exist two different kinds of products:

Single:

A Single is a product whose final payoff depends on the development of **1** underlying asset with respect to a lower barrier. Additionally, the product **always** offers a fixed coupon x (x% of 100 ECU) independently of the development of the underlying asset. In total, the buyer's payoff depends on the following two scenarios:

Scenario 1: If the underlying asset never hits the lower barrier, the buyer receives 100 ECU plus the guaranteed fixed coupon x.

Scenario 2: If the underlying asset hits the lower barrier at least once, the buyer receives the lower amount of **either** 100 ECU **or** the final value of the asset, plus, in each case, the guaranteed fixed coupon x.

Multi:

A Multi is a product whose final payoff depends on the development of **2 independent** underlying assets with respect to a lower barrier. Additionally, the product **always** offers a fixed coupon x (x% of 100 ECU) independently of the development of the 2 underlying assets. In total, the buyer's payoff depends on the following two scenarios:

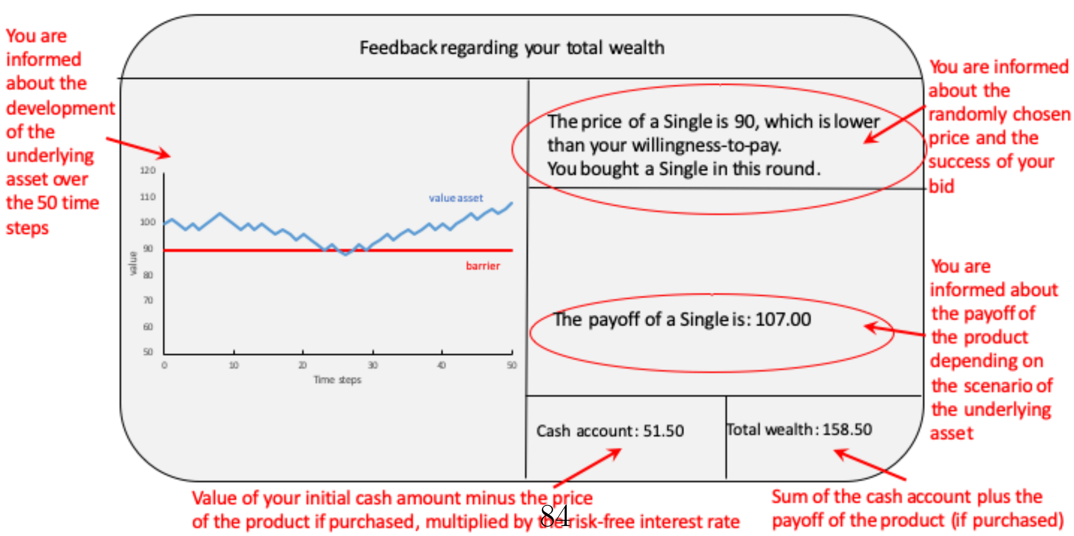
Scenario 1: If none of the 2 underlying assets hits the lower barrier, the buyer receives 100 ECU plus the guaranteed fixed coupon x.

Scenario 2: If **at least 1** of the 2 underlying assets hits the lower barrier at least once, the buyer receives the lower amount of **either** 100 ECU **or** the **worst** performing underlying asset, plus, in each case, the guaranteed fixed coupon x.

The expected payoff for both product types can always be decomposed into the following 4 components:

*Expected payoff = Prob(Barrier hit) * expected payoff(Barrier hit) + Prob(Barrier not hit) * payoff(Barrier not hit)*

<u>Example screen of stage 2:</u>



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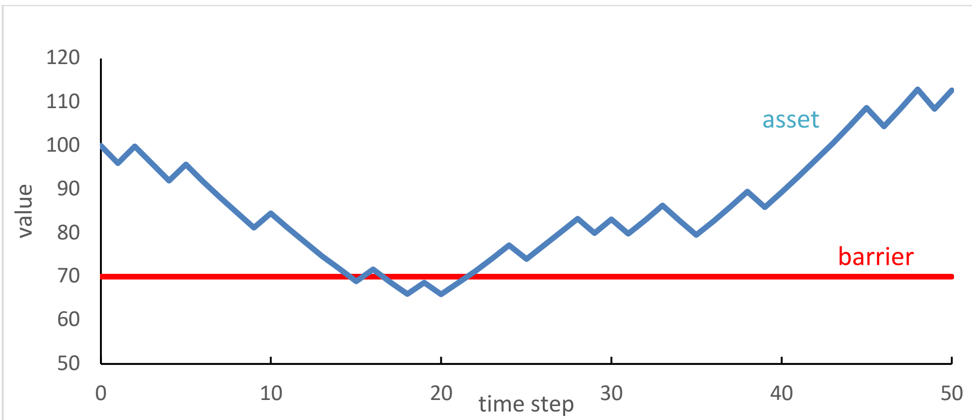
Bonus points: You are guaranteed to earn 0.5 bonus points for participating in this experiment. Besides, you can gain additional bonus points based on your investment decision. You can infer from the distributed table, how many ECUs in a given round correspond to how many bonus points. At the end of the experiment, only **one** of the 12 independent rounds will be randomly selected. Your total wealth from this round will then be converted into bonus points and credited to you at the final exam.

Please answer the following 3 comprehension questions:

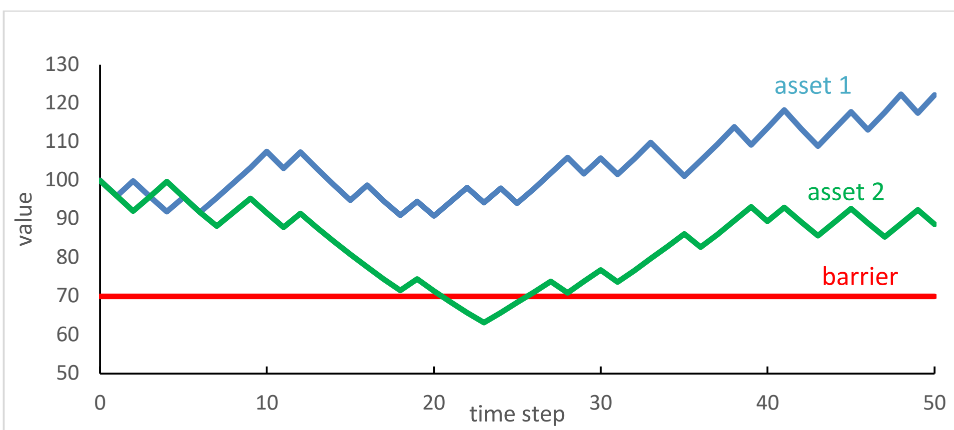
1) Your initial cash amount is 140 ECU. The computer has randomly selected the Single and randomly set its price equal to 100 ECU. The risk-free interest rate is 20%. Assume you are willing to pay 95 ECU for the Single. What is your total wealth at the end of this period in ECU?________________

2) Assume the following development of the asset underlying a Single:



Which scenario has realized? Scenario 1 O Scenario 2 O

3) Assume the following development of the assets underlying a Multi:



Which scenario has realized? Scenario 1 O Scenario 2 O

****

You will now go through a short training session to get familiar with the task. This training session will **not** impact your bonus points.

Mutual Funds and Qualitative Disclosure

Joint with Timo Schäfer[†]

In this paper, we use the content of U.S. mutual funds' prospectuses to examine the informational value of funds' qualitative disclosures. We document significant heterogeneity in the cross-section of funds' qualitative disclosures, primarily attributed to characteristics at the investment company level. Using textual analysis, we decompose funds' qualitative disclosures into informative and standard content. Our results show that funds' risk-taking behavior and risk-adjusted-performance increase with the informativeness of their disclosures. Content-based updates of disclosures are informative about funds' future risk-taking and their future performance. Finally, we document evidence that investors react to some extent to the informativeness of fund disclosures.

3.1 Introduction

The Securities and Exchange Commission (SEC) in the U.S. requires investment companies of mutual funds to disclose qualitative information about several fund characteristics in their annually updated prospectuses. Besides providing quantitative information

[†]Jonathan Krakow, Department of Banking and Finance, University of Zurich, Plattenstrasse 32, CH-8032 Zurich, Switzerland. Email: jonathan.krakow@bf.uzh.ch. Jonathan Krakow acknowledges financial support from the Forschungskredit of the University of Zurich, grant no. [FK-17-015]; Timo Schäfer, Department of Business Informatics and Information Economics, Goethe University Frankfurt, Theodor-W.-Adorno-Platz 4, D-60323 Frankfurt am Main, Germany. Email: t.schaefer@wiwi.uni-frankfurt.de.
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on a fund's risk, performance, and expenses, investment companies disclose textual information on each fund's principal risks, its investment strategy, and its primary investment objective. However, despite the large mutual funds market in the U.S., i.e., \$17.7 trillion of total net assets invested in mutual funds at the end of 2018,[47] the value of qualitative disclosure in funds' prospectuses has not been investigated in academic literature. Importantly, there is no empirical evidence whether mutual funds' qualitative disclosures are informative to investors and whether investors react to it.

According to several studies conducted by the Investment Company Institute (ICI), the information disclosed in a fund's prospectus is a relatively important source of information for investors (Investment Company Institute 2006; 2019). In particular, 34% of mutual fund shareholders rely on information in the prospectus to make an investment decision, and even 90% of mutual fund-owning U.S. households study the investment objective and risks associated with investing in a specific fund.

To simplify an investor's investment decision, the SEC enacted a rule on disclosing key information in a summary section at the beginning of a fund's statutory prospectus (SEC, 2009). The aim of introducing such a summary section is to provide particularly retail investors with key information in a user-friendly and concise format, assisting them in making an informed investment decision. It should make it simpler for investors to find, compare, and interpret information related to a fund's risks and performance, as compared to studying the full statutory prospectus.

In this paper, we use methods from textual analysis to examine the qualitative content provided in summary sections of funds' statutory prospectuses by focusing on the informativeness of funds' disclosures. More precisely, we investigate the summary sections in the statutory prospectuses of active U.S. open-end equity funds between 2011 and 2018.

Our analyses focus on examining the value of these qualitative disclosures for investors and especially whether this information is beneficial from an investor's perspective when making an investment decision. For this purpose, we use a unique feature of funds disclosure – our so-called "laboratory setting". In this setting, we exploit the fact that most investment companies manage several funds and issue a prospectus for each of the funds separately. Accordingly, our laboratory setting provides us with a powerful comparative universe. It allows us to determine whether investment companies provide the same disclosure for each fund under management or whether they tailor the disclosure to each specific fund. Therefore, we do not conceive informativeness in absolute units but as a

[47] For a detailed view on the annual statistics, see "2019 Investment Company Fact Book", available at https://www.icifactbook.org.

relative measure within a comparative universe. More precisely, we say a fund's qualitative disclosure is informative when its content is not addressed by the disclosures of the other funds managed by the same investment company or by other funds in the same fund category. This differentiation is the key idea behind our concept of informativeness of funds' disclosure, and hence the focus of this paper. Moreover, in the context of boilerplate disclosure, our clear advantage is to express informativeness relative to other disclosures instead of defining *a priori* text phrases (e.g., Lang and Stice-Lawrence, 2015).

To highlight the importance of our laboratory setting, we start by measuring the informativeness of funds' disclosed risk. Risk disclosures are often criticized for being subjective and ambiguous (Schrand and Elliott, 1998; Jorgensen and Kirschenheiter, 2003; Kravet and Muslu, 2013), making it difficult for investors to compare them and to verify their accuracy. We address this challenge by using the power of our laboratory setting. We investigate the accuracy of funds' disclosed risk in their prospectuses and at the same time control for the managing investment company of a fund. Our starting hypothesis is that a longer risk disclosure of a fund corresponds to a fund's higher risk-taking (Campbell, Chen, Dhaliwal, Lu, and Steele, 2014). Indeed, we find that a fund's amount of text on disclosed risk is positively and significantly related to its idiosyncratic risk, systematic risk, and general risk, supporting our predictions. Importantly, we find that a large proportion of the cross-sectional variation of funds' risk disclosure is attributable to investment company fixed effects. These two findings are interrelated, as the positive relation only holds when we rely on variation within investment companies. A number of robustness tests confirm this finding.

Next, we examine the actual written content of funds' disclosure. For this, we use our laboratory setting in a more finely tuned analysis to determine how similar the textual content of funds' disclosure is. We document that a large part of funds' disclosure text similarity is due to time-invariant characteristics at the investment company level and less due to fund category effects or time effects. This result is valid for all sections in a fund's prospectus – risk statements, primary objectives, and strategy narratives. Nevertheless, more than one-third of the variation in the similarity of funds' disclosures is due to fund-specific characteristics, indicating that funds' disclosures still contain information relevant to the respective funds.

We use this analysis as a motivation to identify the level of informativeness of funds' disclosures in more detail. Namely, we decompose the textual information in funds' prospectuses into an informative and a standard component along the investment company dimension and the fund category dimension (Hanley and Hoberg, 2010). We argue that the more (less) similar a fund's disclosure is compared to all the other funds' disclosures by the same investment company, the less (more) informative is that specific disclosure. To understand our approach better, we exemplary provide the risk disclosures of two funds managed by the same company (see Appendix A.3). Though the two funds, the Torray Fund and the Torray Resolute Fund, belong to different fund categories and are subject to different sets of risks, they provide exactly the same risk disclosure. Consequently, investors do not learn anything qualitatively fund-specific about the two funds' different risk exposures. Therefore, we consider the informativeness of these disclosures to be limited.[48]

We then turn to the fund-specific informativeness of qualitative disclosure and analyze its implications regarding funds' risk-taking behavior, performance, and flows. First, our results demonstrate that funds with more informative disclosures are subject to higher risk-taking. In particular, our findings show that a fund's idiosyncratic risk increases with regard to the informativeness of its risk disclosures. Next, we examine the implications of informative updates in funds' prospectuses over time. Since funds are supposed to update their prospectus once a year, we have yearly snapshots of their qualitative disclosures that we can track over time. This analysis is also motivated by a guidance update provided by the SEC in 2016 that points to the relevance of timely updates of funds' qualitative information in their prospectuses regarding changes in market conditions a fund is exposed to.[49]

Similar to disclosure informativeness in the cross-section of funds, we look at yearly updates of qualitative disclosures in funds' prospectuses. As we observe an overall increase in funds' disclosure length from one year to the next, our analysis aims at examining whether updated disclosures are informative to investors. For example Appendix B.3 presents for the strategy statement of the Torray Fund an update from 2013 to 2014. Our regression results indicate a negative relation between updates in funds' disclosures and their future risk-taking. This finding suggests that funds with substantial disclosure updates in their prospectuses decrease more strongly their future risk-taking relative to the current level. These two findings are good news for investors. On the one hand, funds that are exposed to higher risks provide investors with more informative (and less standard)

[48]Note that they still can be relatively informative compared to the other funds in their respective fund categories.

[49]See the guidance update by the SEC, March 2016, available at https://www.sec.gov/investment/imguidance-2016-02.pdf.

risk disclosures. On the other hand, updates in funds' disclosures predict changes in funds' future risk.

Second, turning to the performance of funds, we find that a fund's risk-adjusted performance is positively related to the informativeness of a fund's risk and strategy statements. Our results reveal that the effect of the risk statement's informativeness is additive to the effect coming from the informativeness of the strategy statement. Thus, our finding is not driven by the uniqueness of a fund's strategy description but can be traced back to the informativeness in a fund's risk disclosure (Kostovetsky and Warner, 2020). In line with our risk update analysis, we then investigate the predictive power of updates on funds' performance. *A priori* it is not clear whether updates of funds' qualitative disclosures are informative to investors about future fund performance or not (Brown and Tucker, 2011; Cohen et al., 2020). When we look at funds' disclosure updates from one year to the next, we find that particularly funds' adjustments in their strategy statements are economically and statistically significant in predicting future risk-adjusted performance. A content-based change of 4% (mean value in our sample) results in a fund's performance increase by approximately 14 basis points in the next year. Thus, our results suggest that updates in funds' qualitative disclosure, i.e., strategy disclosure, provide relevant information in predicting future performance.

Third, we investigate whether investors take the informativeness of funds' disclosure into account when investing in funds. Our findings suggest that investors can – at least to some extent – differentiate between informative and standard disclosures. We find some statistical evidence that investors increase (decrease) their investment in funds with more informative (standard) disclosures in prospectuses. Moreover, we find a positive and statistically significant effect of funds' provision of a summary prospectus on fund flows. This relation indicates that funds that voluntarily disclose the summary section as an additional filing, i.e., a summary prospectus, experience higher inflows than funds that do not provide a summary prospectus (Brown, Goetzmann, Liang, and Schwarz, 2008; Kozup, Howlett, and Pagano, 2008). Nevertheless, we want to emphasize that it is rather challenging for investors to identify the degree of informativeness of mutual fund prospectuses and to identify informative updates.

Our paper builds on several strands of the literature. First, we add to the recent literature on qualitative (risk) disclosures and their informational value. Previous research, however, rather examines qualitative disclosures in a corporate setting (Dye, 2001; Healy and Palepu, 2001; Verrecchia, 2001). Dyer, Lang, and Stice-Lawrence (2017) document that companies' 10-K filings have become not only longer but also more complex over time. Campbell et al. (2014) and Chiu, Guan, and Kim (2018) analyze risk factor disclosures (RFD) in 10-K filings and conclude that the information that companies disclose in their risk factor section is meaningful. By contrast, Kravet and Muslu (2013) find that RFDs in 10-K filings do not cover firm-level risks, and the content of them is to be more likely boilerplate. These contradictory findings are partially resolved by Bao and Datta (2014). Using a topic modeling approach for RFDs in 10-K filings, they show that only two-thirds of the identified risk types are informative to investors, and not necessarily all of them increase investors' risk perceptions. Similarly, Hope, Hu, and Lu (2016) show by introducing a computing algorithm to quantify the specificity of firms' qualitative risk disclosures that market reactions are positively associated with the quality of those disclosures. In addition to the literature on 10-Ks, Hanley and Hoberg (2010) use methods from textual analysis to examine the information contained in IPO prospectuses, showing that a higher informativeness results in more accurate offer prices. Florysiak and Schandlbauer (2019) conduct a related analysis in the context of ICOs. We extend this literature by examining the informativeness of mutual fund disclosures, which plays a role in the investment decisions of many (retail) investors.

Second, this paper contributes to the large literature on the managerial behavior of fund managers and the following reaction of investors. Several studies (e.g., Jensen, 1968; Carhart, 1997; Wermers, 2003; Berk and Green, 2004; Fama and French, 2010) contribute to the debate whether managers of active funds add value to their investors. Tufano and Sevick (1997) and Fu and Wedge (2011) look closer at the governance of mutual funds and find that the independence of the board positively affects the fee structure. Jain and Wu (2000) and Gallaher, Kaniel, and Starks (2015) show that funds do not experience superior performance after advertising a fund but attract significantly higher fund flows compared to a group of control funds. In line with this finding, Cooper et al. (2005) show that investors react to fund name changes while the corresponding funds do not improve their performance. Therefore, investors react to salient, attention-grabbing information while this information does not necessarily correspond to a higher fund performance (Barber, Odean, and Zheng, 2005). Brown et al. (2008) empirically examine the value of information about operational risk and conflict of interest variables disclosed by hedge funds. Their results suggest that financial institutions and sophisticated investors may receive little added value from mandatory disclosures, while retail investors might benefit from them. Furthermore, the literature shows that funds change their risk-taking behavior over time (e.g., Brown and Goetzmann, 1997; Huang, Sialm, and Zhang, 2011). For instance, Huang et al. (2011) show that funds that shift their risks perform worse than funds with unchanged exposed risks. Our paper examines a different source of information that funds provide to investors: textual disclosure in their prospectuses and its relation to a fund's performance and risk-taking.

Third, our paper adds to the textual analysis literature in general,[50] and to the recent research stream on the qualitative communication of mutual funds in particular (Daughdrill, 2015; Hillert, Niessen-Ruenzi, and Ruenzi, 2016; Hwang and Kim, 2017; Kostovetsky and Warner, 2020).[51] Hillert et al. (2016) provide evidence that investors react to the writing style of shareholder letters, which is another written communication channel of fund managers with their investors besides prospectuses. Hwang and Kim (2017) show that harder-to-read shareholder reports from closed-end investment companies have a negative effect on firm value. Probably closest to our paper is Kostovetsky and Warner (2020). They use the text in funds' strategy statements in their prospectuses to approximate a fund's innovativeness and find that more unique funds attract higher fund flows. Despite the large literature on mutual fund risk, flows, and performance, no previous research has – to the best of our knowledge – systematically studied the informativeness of mandatory qualitative disclosure in the mutual fund industry. This paper is the first that investigates qualitative disclosure in prospectuses by using methods from textual analysis.[52] We provide evidence for the informativeness of these disclosures in the cross-section of funds and over time.

The remainder of the paper is structured as follows. Section 3.2 provides background information about the summary section in U.S. mutual funds' prospectuses and describes the data. Section 3.3 provides general descriptive evidence of funds' qualitative disclosures and introduces our textual informativeness measures. We first explain our laboratory setting, then analyze determinants of funds' disclosed amount of text on risk to motivate our setting, and later introduce our fund-specific informativeness measures. Then, Section 3.4 examines the relation of our informativeness measure with funds managerial behavior and investors' reactions. Finally, Section 3.5 concludes.

[50] See Tetlock (2014) and Loughran and McDonald (2016) for an overview.

[51] Abis (2017) and Baghai, Becker, and Pitschner (2019) extract the information from funds' prospectuses to obtain a proxy for funds' style classification and use of credit ratings, respectively.

[52] Tucker and Xia (2020) examine the content of summary prospectuses with respect to their readability and show that these prospectuses are hard to read.

3.2 Institutional Framework and Data

This section first provides background information on the mandatory provision of a summary section in U.S. mutual funds' prospectuses. Second, we describe how we obtain our prospectus data and preprocess it. Third, we provide summary statistics on the main financial and textual characteristics of our sample of active U.S. equity funds.

3.2.1 Institutional Background

The SEC requires all investment companies to provide a statutory prospectus. This applies to all funds registered under the Investment Company Act of 1940 and that offer their shares under the Securities Act of 1933. In the statutory prospectus, funds inform investors about their past and future activities. The goal is to protect investors by disclosing relevant information about the offered securities.[53] However, these statutory prospectuses are often criticized as long and complicated, using a complex and legalistic language. This results in difficulties for investors to use them efficiently and compare different funds. Accordingly, in April 2009, the SEC adopted a new disclosure framework that requires mutual funds to provide from January 2010 onward a summary section in their statutory prospectuses for securities that they offer for sale (SEC, 2009).

This summary section at the beginning of the statutory prospectus is intended to provide key information to investors facing a large universe of available funds. The information should be easy to understand and relevant for making an informed investment decision. The summary section shows a standardized order and contains streamlined details on the following dimensions: (1) investment objectives; (2) costs and fees; (3) principal investment strategies, risks, and performance; (4) investment advisers and portfolio managers; (5) brief purchase, sale and tax information; as well as (6) information on financial intermediary compensation. Already prior to 2009, open-end mutual funds in the U.S. were required to provide a risk-return summary (SEC, 1998). However, this information was disclosed at the fund family level and, therefore, less informative to investors, as it often describes more than one fund and is not fund-specific.

With the adoption of the new disclosure rule in 2009, investment companies have to inform about each fund's specific investment strategy, risks, and objective. These three sections are at the focus of this paper. Additionally, investment companies can decide

[53] The statutory prospectus is defined in the Securities Act of 1933, see http://legcounsel.house.gov/Comps/Securities%20Act%20Of%201933.pdf.

whether to publish a separate summary prospectus, which contains the same information as the summary section in the statutory prospectus, but is filed separately.[54] Thus, if an investment company manages several funds, the investment company has to publish for each fund a separate summary section. Appendix A.3 and B.3 present examples of funds' qualitative disclosures from their summary section in their respective prospectuses.[55]

Moreover, for our analysis, it is important that mutual funds are required by the SEC to update their summary sections – to react to changes over time – at least once per year. This does not automatically mean that they have to provide new information in each new publication, as it is, for example, the case with mutual fund shareholder letters. In these letters, fund managers discuss the fund's performance and economic outlook (Hillert et al., 2016). However, the SEC also comments that investment companies are supposed to review their risk disclosures when the market conditions of a fund change.

3.2.2 Data

We obtain data on mutual funds' prospectuses from the SEC "Mutual Fund Prospectus Risk/Return Summary Data Sets" (MFSD).[56] This dataset provides quarterly updates of textual and numeric information that is extracted from the risk/return summary sections of mutual funds' prospectuses. Since the values of some text variables are truncated (the maximal length of values is fixed to 2048 bytes), we download prospectus data separately, i.e., filings 497[57] (initial registration) and 485BPOS[58] (post-effective amendment), that is specified in the MFSD dataset.[59]

Prospectus data is provided in the eXtensible Business Reporting Language (XBRL) format. The relevant sections in a prospectus can be identified due to the XBRL tree

[54] While providing a summary section in the statutory prospectus is mandatory, the additional delivery of a summary prospectus is not. However, about 85% of all mutual funds offered a summary prospectus to investors by the end of 2018.

[55] Note, many funds are also offered in multiple share classes. Since all share classes are invested in the same underlying portfolio, this separation of individual summary sections does not apply to multiple share classes. All share classes of a fund are pursuing the same strategy and are exposed to the same risks. They primarily differ in their fees, for example, their management fees and 12b-1 fees.

[56] The dataset is available at https://www.sec.gov/dera/data/mutual-fund-prospectus-risk-return-summary-data-sets.

[57] https://www.law.cornell.edu/cfr/text/17/230.497

[58] https://www.law.cornell.edu/cfr/text/17/230.485

[59] For some funds, we observe several 485BPOS filings per year. In these cases, in line with Baghai et al. (2019), we only keep the prospectus with the longest risk statement for each fund and year. Regarding the length, we refer to the number of words after removing the html code from the filings, while Baghai et al. (2019) refer to the number of sentences.

and key structure. We extract the most recent data on a fund's risk statement, strategy statement, and investment objective for each fund and year. We clean text data by removing *html* code, stem words, and by converting numeric values into <*numeric*>.

The final sample comprises all active U.S. open-end mutual funds regulated under the supervision of the SEC from 2011 to 2018 that we match with the Morningstar database, covering a total of 1,892 funds. For our empirical analysis regarding the informativeness of funds' qualitative disclosure, we merge mutual funds' prospectus data from the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system from the SEC[60] with the Morningstar survivorship bias-free mutual fund database. The Morningstar database includes information on fund returns, various risk measures, as well as several other mutual fund characteristics, like total assets under management and fees.

We merge the prospectus data from the SEC with the database in Morningstar by using a fund's ticker symbol at the share class level. Since Morningstar provides data by fund's share class, we aggregate the quantitative characteristics of a fund's share classes into a single fund characteristic by taking the value-weighted average (see, e.g., Kacperczyk, Sialm, and Zheng (2008); Nohel, Wang, and Zheng (2010); Gallaher et al. (2015); Choi, Kahraman, and Mukherjee (2016)). For the mapping we use the investment companies' file of the SEC to identify 40,266 ticker symbols of share classes under their regulation (see Table 3.12 in the Appendix for details on the matching process).[61] After excluding funds with missing ticker symbols in Morningstar and linking them to to the SEC, it reduces the sample to 8,542 unique mutual funds from 2011 to 2018. We conduct several plausibility tests to ensure that the data in Morningstar corresponds to the funds identified in the SEC reports.[62] Next, we drop all balanced funds, money market funds, fixed income funds, index funds, and exchange traded funds. So in our final sample, we focus on active U.S. open-end equity funds for reasons of comparability. Finally, we also exclude observations where a fund's total net assets in a given year are less than USD 1 million. Our final sample of interest then comprises 1,892 active U.S. equity open-end mutual funds from 2011 to 2018.

Table 3.1 reports the summary statistics on turnover, risk, and returns of funds in our sample of active U.S. equity funds. We also include a fund's age (in months), its expense

[60](https://www.sec.gov/edgar/)

[61]The basic identification information on investment companies year by year is available at https://www.sec.gov/open/datasets-investment_company.html.

[62]For instance, we test whether there is a unique link between a fund's Series ID in EDGAR and assigned Fund ID in Morningstar. Since both identifiers are unique at the fund level, we exclude cases where Series IDs are assigned to multiple Fund IDs in Morningstar in a year.

ratio, and its size to analyze whether more established funds, more expensive funds, and larger funds differ in their disclosure behavior. Based on data on total net assets and returns, we then compute yearly fund net flows, which we define as the growth rate of the total assets under management adjusted for reinvested returns:

$$Flow_{f,t} = \frac{TNA_{f,t} - TNA_{f,t-1}(1 + RF_{f,t})}{TNA_{f,t-1}(1 + RF_{f,t})}, \tag{3.1}$$

where $TNA_{f,t}$ is fund f's total net assets at time t and $RF_{f,t}$ is the fund's return over the prior year.[63] To account for outliers, we winsorize at both the bottom and the top parts of the distribution at the 1% level.

The average active U.S. equity fund in our sample has total net assets of USD 2,213 million, is about 17.5 years old, and charges an annual expense ratio of 0.64%. An investor's average yearly return of funds in our sample is 4.64%, while the average fund's risk, estimated as the standard deviation of the fund's monthly returns over the prior 36 months, amounts to 2.16. The remainder of the table shows summary statistics on risk variables and the length of the summary section of the prospectuses.[64]

Next, we turn to the textual data. We extract all risk statements, strategy statements, and investment objectives from the summary sections of funds' prospectuses between 2011 and 2018 to investigate the information content of funds' prospectuses both in the cross-section and over time. Figure 3.1 illustrates time trends and differences between the three sections of our focus. It presents the median statistics of the length of each of the sections between 2011 and 2018 for the risk statement (Panel A), the strategy statement (Panel B), and the investment objective (Panel C), respectively. Panel D displays aggregated numbers.

Panel A of Figure 3.1 provides evidence that the length of the average risk disclosure section has grown significantly between 2011 and 2018. While the median section contains about 402 words in 2011, the number has almost grown by 50% until the end of 2018. We document a similar growth for funds' strategy statements in Panel B, whereas funds' investment objectives do not show considerable variation over time and represent by far the shortest of the three sections.

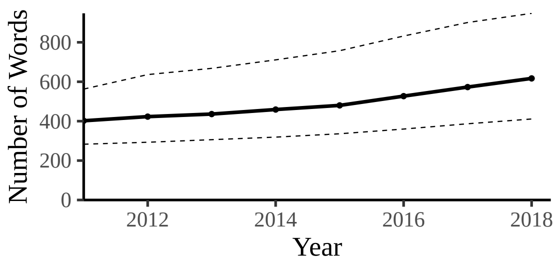
[63] This measure follows the methodology of Huang et al. (2011) and ensures that fund flows cannot be below -100%. Most studies define fund's net flows as Flow = $(TNA_{f,t} - TNA_{f,t-1}(1+RF_{f,t}))/(TNA_{f,t-1})$. This approach guarantees that fund outflows will not be below -100%. The Pearson correlation coefficient between the two measures is 0.998.

[64] All variables are defined in detail in Table 3.15.

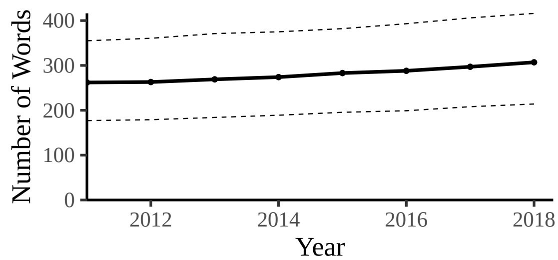
Table 3.1: **Summary statistics active U.S. equity funds**

Table 3.1 shows summary statistics (mean, standard deviation, median, 1% (p1) and 99% percentile (p99) percentile, and the number of observations for all financial characteristics of active U.S. equity funds in our sample at the fund-year level. Our sample includes all active U.S. equity mutual funds in the SEC database that are linked to a fund in the Morningstar database, i.e., 1,892 funds between 2011 and 2018. The variable *Fund Flow Period* are fund flows over the 12 months in the respective calendar year and is winsorized at the bottom and the top percentile. *Fund Size* is a fund's total net assets (TNA) in million USD. *Company Size* is the sum of all funds' TNAs an investment company manages. *Age* is a fund's age in months and is calculated based on the IPO date of the oldest share class. *Expense Ratio* is a fund's annual expense ratio in percent. *Turnover Ratio* is a fund's average ratio of purchases or sales to TNA. *Raw Return* is the fund's return calculated as the change in yearly net asset value minus the fund's cost. *Fund Risk* is the standard deviation of a fund's monthly returns over the prior 36 months. *Systematic Risk* is a fund's market beta from estimating a 4-factor Carhart (1997) model using a fund's returns from the prior 36 months. *Idiosyncratic Risk* is the standard deviation of the residuals from this regression. *# of Words* is the number of words in the summary section. All fund characteristics are defined in more detail in Table 3.15 in the Appendix.

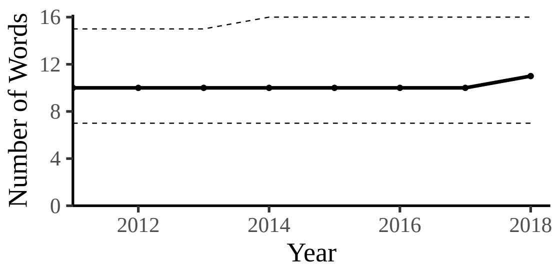
Variable name	Mean	Std	p1	Median	p99	N
Fund Flow Period (in %)	1.82	31.88	-67.50	-2.45	109.58	8,979
Fund Size (in mn.)	2,213.29	7,960.45	3.01	427.45	33,925.49	8,979
log(Fund Size (in mn.))	19.76	2.00	14.90	19.87	24.25	8,979
log(Company Size)	23.68	2.32	17.00	23.94	28.47	8,979
Age (in Months)	209.84	154.07	22.50	186.50	941.50	8,979
log(Age (in Months))	5.11	0.73	3.10	5.23	6.85	8,979
Expense Ratio (in %)	0.64	0.83	0.06	0.42	2.95	8,979
Turnover Ratio (in %)	64.32	72.30	2.00	48.00	308.24	8,979
Raw Return (in %)	4.64	8.60	-12.39	2.65	33.62	8,979
Fund Risk (in %)	2.16	1.60	0.30	1.61	6.83	8,979
Systematic Risk	0.51	0.34	0.09	0.39	1.20	8,979
Idiosyncratic Risk (in %)	0.57	0.53	0.06	0.40	2.29	8,979
# of Words	565.73	399.24	132.00	457.00	1987.00	8,979
log(# of Words)	6.15	0.61	4.88	6.12	7.59	8,979



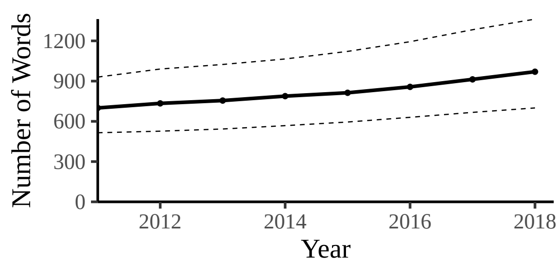
(a) **Panel A: Risk statement**



(b) **Panel B: Strategy statement**



(c) **Panel C: Investment objective**



(d) **Panel D: All sections**

Figure 3.1: **Distribution of number of words in funds' qualitative disclosures**

Figure 3.1 shows the median of number of words in qualitative disclosures of prospectuses of active U.S. equity funds over time. The number of words is calculated after removing the html code from the filings. Panel A, B, and C show the evolution for funds' risk statement, strategy statement, and investment objective of funds' summary sections in their yearly prospectuses, respectively. Panel D shows the aggregated length of all three sections from Panels A–C. Dashed lines indicate 25% and 75% percentiles.

3.3 Descriptive Evidence of Funds' Risk Disclosures

In this section, we provide descriptive evidence on the information in funds' qualitative disclosures. Section 3.3.1 introduces the laboratory setting that we use throughout the analysis. Then, we use this setting in Section 3.3.2 to examine variation in the disclosure length in the cross-section of our sample of active U.S. equity funds. Sections 3.3.3, 3.3.4, and 3.3.5 introduce our detailed measures to approximate the informative and standard content of funds' qualitative disclosures in the cross-section and over time.

3.3.1 Laboratory Setting

In this study, we use a unique laboratory setting to allow us to pinpoint the degree of informativeness in funds' qualitative disclosures. Our setting comprises investment companies that (usually) manage several funds. Importantly, they have to provide investors with summarized information for each fund separately, see Section 3.2. This specific characteristic enables us to compare qualitative disclosures from a completely new perspective. More specifically, we can compare the disclosures of funds managed by the same investment company to determine the level of fund-specific information. To illustrate this setting, we briefly describe two cases. In one case, an investment company could use a generic template for the qualitative disclosures of the funds that it manages. For instance, an investment company discloses the same risk statements for all its funds, though the funds of that company differ in their investment strategies (see as an example the risk statements of the Torray Fund and the Torray Resolute Fund in Appendix A.3). Such risk disclosures would be relatively uninformative to investors, as the investment company does not provide much fund-specific information. In the other case, the investment company could tailor funds' disclosures to fund-specific characteristics. Then, investors can actually derive valuable information about a fund's risks when reading the information.

Therefore, to exploit our laboratory setting, we collect information on the investment company for each fund. The SEC assigns identifying Central Index Key (CIK) numbers to investment companies, which is provided in EDGAR. The CIK refers to the unique investment company identifier. However, several CIKs might refer to the same underlying investment company, which would bias our results when comparing funds' disclosures within the same CIK. For instance, Vanguard's funds have different CIKs, but all belong to the Vanguard Group, e.g., Vanguard Explorer Funds and Vanguard World Fund. Hence, to avoid a potential bias in our results, we use EDGAR searches and Internet searches and

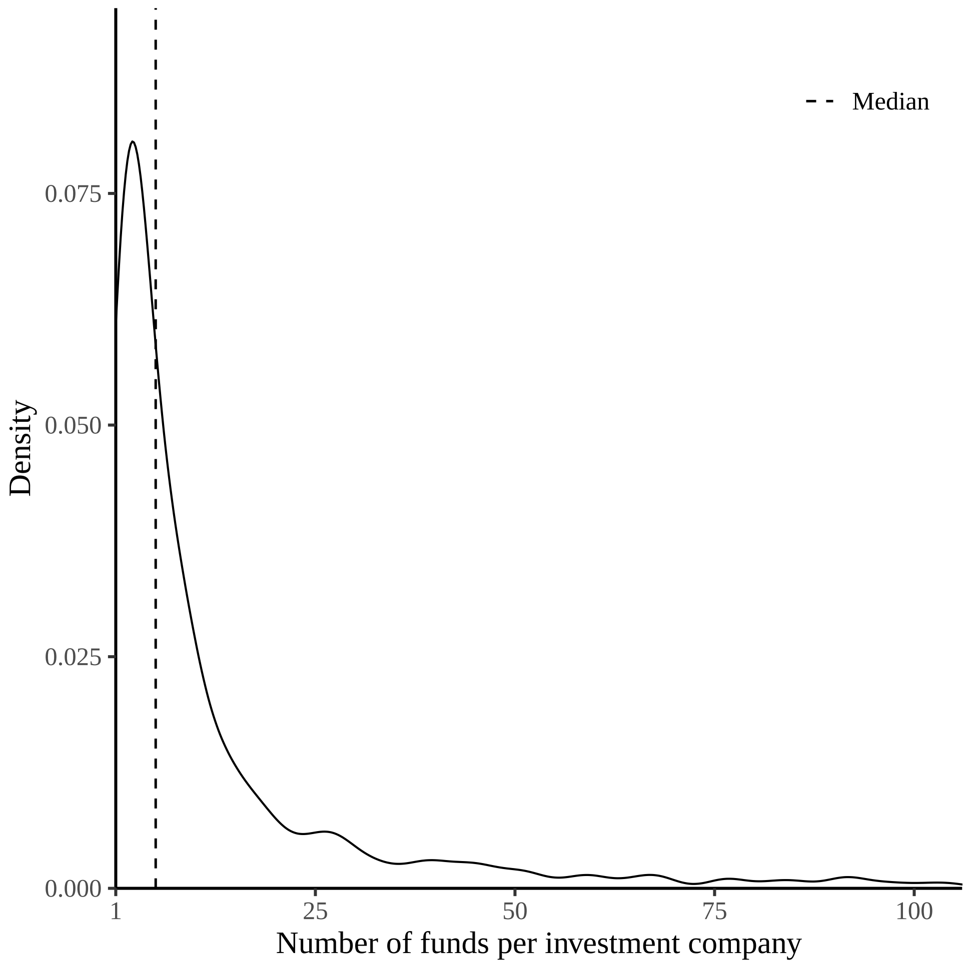


Figure 3.2: **Density distribution of funds per investment company**

Figure 3.2 shows the distribution of funds per investment company in our sample. For companies that have different numbers of funds across years, we use the maximum value. In total there are 442 investment companies. For illustrative reasons, we exclude two investment companies from Figure 3.2 with 144 and 299 funds, respectively. The vertical line marks the median number of funds per investment company (5).

manually map funds to their investment companies. Figure 3.2 illustrates the distribution of the number of funds per investment company.

In general, an investment company manages several funds. A few small investment companies manage only a single fund, while the largest investment companies are responsible for managing more than 100 funds. The median number of funds per investment company is 5. Therefore, to measure the informativeness of a fund's disclosure, we compare the content on average with 4 other fund disclosures of the same investment company.

3.3.2 Determinants of Funds' Disclosures

The amount of text on risk disclosure is highly heterogeneous in the cross-section of funds as measured by the number of words. More precisely, we document that the length of funds' risk disclosures varies from 200 words to more than 7,000 words (see also Panel A of Figure 3.4 in the Appendix C.3). The number of words is a relatively simple but meaningful text-based measure of risk disclosure. The textual content in prospectuses' risk sections is usually divided into several risk factors, e.g., a fund reports its exposure to blue-chip risk or foreign investment risk. Therefore, we assume that the length of a fund's risk statement and the number of disclosed risk factors are positively correlated, meaning that longer risk statements contain more risk factors. Nevertheless, it is not clear what determines this heterogeneity in risk disclosures in the cross-section of funds. Accordingly, we ask whether the exposed risk of a fund's portfolio, assuming that riskier funds provide longer risk disclosures, explains this heterogeneity. We hypothesize that funds with relatively similar investment strategies are subject to the same set of risks and therefore provide similar amounts of risk disclosure. To shed light on this hypothesis and to motivate our first analysis, we look at a group of very similar funds: S&P 500 Index funds (Hortaçsu and Syverson, 2004). Panel B of Figure 3.4 in the Appendix C.3 displays the distribution of risk disclosure of S&P 500 Index funds in our overall sample for the year 2018. It clearly shows distinct differences in the length of funds' risk disclosures in spite of the funds' identical strategies.

In line with this finding, a report by the SEC points to considerable variation of risk disclosures of funds belonging to the same Morningstar category.[65] Accordingly, we can use our laboratory setting to examine how much of the variation in the length of funds' risk disclosure is determined at the investment company level while controlling for several fund characteristics. In general, we would expect that funds with riskier portfolios also write more extensively about their risks (Campbell et al., 2014). Therefore, we hypothesize that funds exposed to larger risks in their portfolios also report more extensively about it in their risk disclosures.

We answer this research question by relating the amount of disclosed risks, i.e., log(Number of Words), as a dependent variable to a fund's exposed risk via its portfolio holdings. We take the logarithm of the number of words since the distribution of risk disclosure is highly skewed (see Panel A in Figure 3.4 in the Appendix C.3). We

[65] See, for instance, the "Request for Comment on Fund Retail Investor Experience and Disclosure", available at https://www.sec.gov/rules/other/2018/33-10503.pdf.

use three different risk measures as dependent variables to represent various dimensions of a fund's risk, i.e., general risk, systematic risk, and idiosyncratic risk. Following the approach suggested by the literature on mutual funds, we measure the general risk of a fund (*Fund Risk*) by calculating the standard deviation of the returns over the prior 36 months as a risk measure (e.g., Huang et al., 2011). Our sample comprises all active U.S. equity funds to derive implications from funds' qualitative disclosure on their managerial behavior. Note, however, that the descriptive evidence we are presenting in Section 3.3.2 generalizes to the whole universe of U.S. mutual funds.

To examine the determinants of a fund's disclosed risk, we run OLS regressions at the fund-year level. We regress the length of a risk statement on the general risk variable. Furthermore, we control for several fund characteristics as well as investment company characteristics like fund flows and returns over the respective calendar year, fund size, expense ratio, turnover ratio, age, and a dummy that indicates whether a fund files a summary prospectus in that year (1) or not (0). Then, we estimate the following panel regression model:

$$\begin{aligned}\log\left(\#\text{ of Words}\right)_{f,t} = &\beta_0 + \beta_1\text{Fund Risk}_{f,t} + \beta_2\text{Fund Flow Period}_{f,t} + \beta_3\text{Return Period}_{f,t}\\ &+ \beta_4\log(\text{Fund Size}_{f,t}) + \beta_5\text{Expense Ratio}_{f,t} + \beta_6\text{Turnover Ratio}_{f,t}\\ &+ \beta_7\log(\text{Age}_{f,t}) + \beta_8\text{SP Dummy}_{f,t} + \nu_{cat} + \nu_t + \nu_{cik} + \epsilon_{f,t},\end{aligned} \tag{3.2}$$

where $\log(\#\text{ of Words})_{f,t}$ is the log of number of words in the disclosed risk statement and $\text{Fund Risk}_{f,t}$ is a fund's general risk of fund f in year t. ν_{cat}, ν_t, and ν_{cik} are fund category, year, and investment company's fixed effects respectively. We cluster standard errors by fund and year. The coefficient of interest β_1 captures the marginal effect of the fund's respective risk on the amount of risk disclosure. It allows us to analyze whether the disclosed risk is positively aligned with the fund's exposed risk dimension.

The inclusion of fixed effects of fund categories allows us to estimate β_1 by exploiting variation in the disclosed risk of funds within a specific fund category. The amount of disclosure might vary substantially across different fund categories, e.g., between small-cap funds and large-cap value funds, which can be distinguished regarding their risk-taking behavior. Time fixed effects allow us to control for the time trend in the length of these statements that we observe in Figure 3.1. Finally, we add investment company fixed effects, considering that different investment companies – irrespective of a fund's exposed risk – provide varying amounts of (risk-related) information. The inclusion of an investment company fixed effect enables us to investigate the role of a fund's investment company in more detail concerning the decision of the amount of disclosed information. Table 3.2 shows the results obtained by estimating Equation 3.2 for the fund's general risk (Fund $\text{Risk}_{f,t}$) with category, year, and investment company fixed effects.

Table 3.2: **Determinants of length of risk statements - all funds**

Table 3.2 shows the coefficients of OLS regressions with the length of a fund's risk section in its prospectus (*log(# of Words)*) as the dependent variable on various fund characteristics on all funds. *Summary Prospectus* is a dummy indicating whether the fund publishes a summary prospectus (1) or not (0). The control variables are defined in detail in Table 3.15. In the first specification (1), we regress a fund's disclosed risk on fund risk controlling for the fund category fixed effects (Category FE) and year fixed effects (Year FE). In specification (2), we add investment company fixed effects (CIK FE) to the regression. In specification (3), we alternatively control for the interaction of investment company fixed effects and year fixed effects (Year×CIK FE). The sample consists of 29,728 fund year observations between 2011 and 2018. Standard errors are reported in parentheses and are double-clustered at the fund and year level. * , **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable	$\log(\text{\# of Words})_{Risk}$		
	(1)	(2)	(3)
Fund Risk	-0.040^{***}	0.013^{***}	0.015^{***}
	(0.012)	(0.003)	(0.003)
Fund Flow Period	-0.00003	-0.0001^{*}	-0.0001^{**}
	(0.0002)	(0.0001)	(0.0001)
Return Period	-0.003	0.001	0.0002
	(0.002)	(0.001)	(0.001)
log(Fund Size)	-0.024^{***}	0.010^{***}	0.010^{***}
	(0.005)	(0.003)	(0.003)
Expense Ratio	-0.012	-0.016	-0.018
	(0.017)	(0.011)	(0.011)
Turnover Ratio	0.0001^{**}	0.00001	0.00001
	(0.00003)	(0.00001)	(0.00001)
log(Age)	-0.127^{***}	-0.107^{***}	-0.114^{***}
	(0.014)	(0.008)	(0.008)
Summary Prospectus	-0.018	0.046^{**}	0.077^{**}
	(0.047)	(0.022)	(0.030)
Category FE	Y	Y	Y
Year FE	Y	Y	N
CIK FE	N	Y	N
Year×CIK FE	N	N	Y
Observations	29,728	29,728	29,728
R^2	0.354	0.797	0.833

For the results of the first regression, we document a negative relation between disclosed and exposed risk. Specification (1) in Table 3.2 shows that a fund's general risk is negatively related to the amount of disclosed risk when exploiting within a year and within a category variation. A one-unit higher risk measure results, on average, in about a -5.4% decrease in the length of a fund's risk statement, which is statistically significant at the 1% level. This result clearly contrasts our hypothesis that riskier funds inform more extensively about their risk exposure. In specification (2), we additionally control for unobserved characteristics at the managing company level using investment company fixed effects. In line with our expectations, we now document a positive and significant relation between a fund's general risk and the amount of disclosed risk. The change in the sign of the coefficient from specification (1) to (2) implies that riskier funds within the same investment company write more extensively about their risks in their risk statements. Moreover, when comparing specifications (1) and (2), there is a large increase in the R-squared from 0.118 to 0.756, which points to the relevance of unobserved characteristics at the investment company level to explain variation in the amount of risk disclosure. The inclusion of investment company fixed effects significantly increases the R-squared. This fact illustrates that the length of the disclosed risk statements is considerably determined at the investment company level and not exclusively at the fund category level. Accordingly, at this stage, our results suggest that a comparison of funds' disclosed risks across categories and investment companies is rather difficult since we only document a positive relation between a fund's general and disclosed risk when we control for these two dimensions. Finally, specification (3) includes the interacted year×investment company fixed effects, which control for unobserved time-varying characteristics at the investment company level (instead of time-invariant characteristics in specification (2)). Specification (3) confirms our results from specification (2) and shows a positive and significant relation between disclosed risks and general risk. To ensure that investment companies with only one fund do not drive our results, we also exclude those funds in a robustness test. All findings hold qualitatively and are statistically significant. Moreover, our findings documented in this Section can be generalized to the complete sample of U.S. mutual funds; see Table 3.13 in the Appendix.

Besides a fund's general risk, we also examine several other fund characteristics as controls. First, for all specifications in Table 3.2, we find that the coefficient of the age variable is negative and highly significant, which indicates that older funds write relatively shorter risk statements than younger funds. Second, our results reveal that funds with higher turnover, i.e., funds that rebalance their portfolio holdings more extensively, provide longer risk statements. Third, whenever we include investment company fixed effects, we find that larger funds and those that have lower fund inflows provide longer risk statements.

As alternative proxies for funds' risk-taking that might influence the variation in funds' risk disclosures, we distinguish between funds' idiosyncratic risk and systematic risk. In particular, we hypothesize that a fund's idiosyncratic risk is positively related to the fund's risk disclosure length. If a fund exhibits a higher idiosyncratic risk, we would expect that the fund would need more words to explain the fund-specific risks. Similarly, we expect a positive relation when looking at a fund's amount of text on disclosed risks and a fund's systematic risk.

We estimate a 4-factor Carhart (1997) model to compute a fund's market beta as a proxy for its systematic risk since it measures the relation between the fund's excess returns over Treasury bills and excess market returns. We compute the market beta in the 4-factor model based on the fund returns measured in the prior 36 months. To quantify a fund's idiosyncratic risk, we calculate the standard deviation of the residuals from the 4-factor regression as $\sqrt{(1/(T-2))\sum_{t=1}^{T}\epsilon_{f,t}^2}$, where $T = 36$ months and $\epsilon_{f,t}$ is the residual of fund f in month t in the 4-factor model regression. Table 3.3 presents the results from estimating Equation 3.2 with idiosyncratic risk and systematic risk as independent variables, respectively.

In specifications (1) and (4), we use fund category fixed and year fixed effects and find a significantly negative relation between the disclosed risk amount and the exposed risk – either for the idiosyncratic risk or the systematic risk, respectively. Once again, when we control for investment company fixed effects as in specifications (2)–(3) and (5)–(6), the sign of the risk coefficient changes from negative to positive and becomes highly significant. Therefore, the results in Table 3.3 show that the amount of disclosed risks is positively related to a fund's idiosyncratic risk controlling for unobserved investment company characteristics. The higher the idiosyncratic risk of an active U.S. equity fund in our sample, the more information is disclosed in the fund's risk statement. This finding is robust to either time-invariant (specification (2)) or to time-varying (specification (3)) investment company characteristics. The same holds true for the systematic risk of funds. Overall, our findings indicate that a fund's risk statement, approximated by the length of these risk statements, is reasonably informative when it comes to a fund's exposed risks.

Table 3.3: **Determinants of length of risk statements - idiosyncratic risk and systematic risk**

Table 3.3 shows the coefficients of OLS regressions with the length of the risk section (*log(# of Words)*) as the dependent variable on various fund characteristics. In specifications (1)–(3), we regress the disclosed risk of a fund on the fund's idiosyncratic risk. In specifications (4)–(6), we regress the disclosed risk on the fund's systematic risk. In specifications (1) and (4), we control for the category and year fixed effects. In specifications (2) and (5), we add investment company fixed effects. In specifications (3) and (6), we control for the interaction of investment company fixed effects and year fixed effects. The control variables are defined in detail in Table 3.15. Standard errors are reported in parentheses and are double-clustered at the fund and year level. * , **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable	$\log(\#\text{ of Words})_{Risk}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Idiosyncratic Risk	−7.352**	7.296***	6.994***			
	(2.867)	(1.879)	(1.976)			
Systematic Risk				−0.273***	0.070**	0.089***
				(0.043)	(0.032)	(0.034)
Fund Flow Period/100	-0.0001	−0.0004***	−0.0005***	-0.0003	−0.0004**	−0.0004***
	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Raw Return/100	-0.004*	0.001	-0.0001	0.0004	0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log(Fund Size)	0.010	0.011**	0.012**	0.008	0.011**	0.013**
	(0.009)	(0.005)	(0.005)	(0.008)	(0.005)	(0.005)
log(Company Size)	−0.045***	0.024*		−0.042***	0.022	
	(0.011)	(0.014)		(0.011)	(0.014)	
Expense Ratio	-0.011	0.002	0.001	0.008	0.007	0.004
	(0.016)	(0.008)	(0.009)	(0.015)	(0.008)	(0.009)
Turnover Ratio	0.001***	0.0004***	0.0005***	0.001***	0.0005***	0.0005***
	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
log(Age)	−0.122***	−0.072***	−0.073***	−0.126***	−0.072***	−0.073***
	(0.022)	(0.012)	(0.013)	(0.021)	(0.012)	(0.013)
Summary Prospectus	0.047	0.056*	0.043	0.020	0.057*	0.047
	(0.067)	(0.030)	(0.045)	(0.065)	(0.030)	(0.047)
Category FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	N	Y	Y	N
CIK FE	N	Y	N	N	Y	N
Year×CIK FE	N	N	Y	N	N	Y
Observations	8,979	8,979	8,979	8,979	8,979	8,979
R^2	0.110	0.757	0.823	0.121	0.756	0.822

3.3.3 Cross-sectional Informativeness in Fund Prospectuses

The preceding Section has provided evidence that a large part of the amount of disclosed risks can be traced back to unobserved characteristics at the level of the investment company and at the level of the fund category. To formalize this finding and analyze the comparability and specificity of funds' disclosures, we next examine the similarity of the actual *written* content in funds' prospectuses and the corresponding cross-sectional determinants. A common concept to calculate differences between two text documents is the cosine similarity. Hence, we compute the cosine similarity between the disclosures of two funds' to express the distance between the two text documents (ignoring the order of words in a document).[66] We do this for all three sections separately – risk statement, strategy statement, and primary objective – and for the complete document. The cosine similarity takes a value of 0 (1) in case the two disclosures are entirely different (identical). Formally, we compute the cosine similarity between the disclosures of two different funds f and f' as

$$\text{sim}_{f,f'} = \frac{\vec{V}(\mathbf{d}_f)\vec{V}(\mathbf{d}_{f'})}{||\vec{V}(\mathbf{d}_f)||_2||\vec{V}(\mathbf{d}_{f'})||_2} \quad \in [0,1], \tag{3.3}$$

where $\vec{V}(\mathbf{d}_f)$ is the word vector of fund f in vector space notation using term frequency – inverse document frequency (tf-idf) weights and $||\cdot||_2$ is the L_2 norm for normalization. Intuitively, the cosine similarity tells us how different two text documents are by calculating the angle between the two word vectors.[67] In contrast to an equal weighting of words using the vector space operator $\vec{V}(\cdot)$, the tf-idf schema takes into account that some words appear in a large (small) number of funds' prospectuses and thus are assigned a lower (higher) weight.

We conceive a fund's disclosure as less generic the more different a fund's risk disclosure is compared to the risk disclosures of all other funds from the same investment company

[66] For instance, Hoberg and Phillips (2016) use textual similarity measures for text-based industry classifications. Moreover, Cohen et al. (2020) compute the textual similarity between companies' annual reports.

[67] For instance, the vector space operator $\vec{V}(\cdot)$ transforms the two sentences $\mathbf{d}_1$=“this is a risk”=(“this”, “is”, “a”, “risk”)$'$ and $\mathbf{d}_2$=“this is no problem”=(“this”, “is”, “no”, “problem”)$'$ into word vectors in the same vector space, i.e., $\vec{V}(\mathbf{d}_1) = (1,1,1,1,0,0)'$ and $\vec{V}(\mathbf{d}_2) = (1,1,0,0,1,1)'$. Then, the first element of the vector $\vec{V}(\mathbf{d}_1)$ is the count of the word “this” in document $\mathbf{d}_1$, the second element refers to the word “is”, and the sixth element to the word “problem”. This transformation using the operator $\vec{V}(\cdot)$ allows us to compare the two documents in the same vector space and quantify their similarity using the definition of cosine similarity in Equation 3.3.

or the same fund category. To express this idea of differences across funds' disclosures, we apply the concept of cosine similarity. In particular, we compute the median of a fund's similarity with all other funds in a given year and regress it via OLS on year, investment company, and fund category fixed effects. The regression results allow us to evaluate how much of the variation of a fund's disclosure similarity can be assigned to each of the fixed effects. As the similarity of two funds from the same investment company might be upward biased due to the similarity in a company's writing style, we use only stemmed (proper) nouns in funds' prospectuses and accordingly, do not consider any stylistic words.[68]

This regression exercise is like a clustering problem, in which we aim to understand why some funds' disclosures are similarly different from all other funds. Apart from the risk disclosure statement, we also consider the primary objective and strategy statement in the summary sections of a funds' prospectuses to generalize our findings to other parts of a fund's prospectus. Table 3.4 presents the results for each of the three parts separately and jointly. Panel A in Table 3.4 comprises the results for the complete U.S. fund universe, while Panel B contains the results for our sample of active U.S. equity funds.

When looking at the whole documents (Panel A of Table 3.4), we find that the most substantial part of the variation in fund's disclosures median similarity materializes at the investment company level (35.51%). In contrast, the contribution of a fund's category is only about a third of the size compared to the investment company effect (9.70%). Nevertheless, the residual contribution is still comparatively high, which suggests that 41.99% of the variation can be traced back to funds' idiosyncratic effects. The majority of fund-level variation can be explained by time-invariant fund characteristics (33.17%). When we consider the three parts of funds' summary prospectuses separately, we document that funds' risk statements are the least fund-specific (38.01%) parts, while funds' strategy statements are more informative to investors. The results in Panel B of Table 3.4 for the sample of active U.S. equity funds hold qualitatively, though the contribution of a fund's category is much smaller, as we focus on a very particular category of funds. In line with our findings in Section 3.3.2, our results suggest that a lot of the content-based variation across funds can be traced back to the investment company of a fund. However, our results also indicate that a substantial part of the textual content of funds' disclosures is fund-specific and is possibly valuable to investors.

[68]We identify (proper) nouns in funds' prospectuses via parts-of-speech (POS) tagging.

Table 3.4: **Variance decomposition using fixed effects**

Table 3.4 shows the coefficients of OLS regressions with a fund's median similarity with all other funds in a given year as the dependent variable on year fixed effects, fund category fixed effects, and investment company fixed effects. The variation that is not explained by the three fixed effects (*Fund-level*) can be divided into fund fixed effects (*Fund FE*) and a residual component (*Residual*) that is not gauged by fund FEs. We disregard singleton observations in this analysis. In Panel A, we provide the results for all funds matched with the Morningstar database and with the information on the fund category. In Panel B, we show the results for our sample of active U.S. equity funds.

Panel A: All funds

	Fraction accounted by (%)			
	All sections	Risk statement	Strategy statement	Primary objective
Year FE	5.08%	7.68%	1.04%	0.31%
Category FE	9.70%	8.74%	9.17%	7.50%
Investment Company FE	35.51%	37.19%	31.57%	37.99%
Fund-level	41.99%	38.01%	51.89%	53.53%
Fund FE	33.17%	28.19%	43.68%	48.96%
Residual	8.82%	9.82%	8.21%	4.56%
Total	100.0%	100.0%	100.0%	100.0%

Panel B: Active U.S. equity funds

	Fraction accounted by (%)			
	All sections	Risk statement	Strategy statement	Primary objective
Year FE	2.60%	5.07%	0.13%	0.78%
Category FE	0.03%	0.11%	0.09%	0.41%
Investment Company FE	58.03%	54.71%	54.16%	62.98%
Fund-level	38.41%	38.75%	45.43%	34.82%
Fund FE	28.84%	25.48%	36.05%	30.09%
Residual	9.58%	13.27%	9.38%	4.73%
Total	100.0%	100.0%	100.0%	100.0%

3.3.4 Decomposition into Standard and Informative Content

But what part of the information in funds' prospectuses is fund-specific and what part is related to the investment company and fund category, respectively? We refer to the fund-specific part as the informative one because this part of the variation is explained neither by the investment company nor by the fund category. Once we have quantified a fund's disclosure's informativeness, we then relate it to a fund's risk-taking, performance, and investors' behavior.

We decompose a prospectus' content into an informative component and a standard component (Hanley and Hoberg, 2010). The standard component has the two dimensions in our setting: the dimension of the investment company and the dimension of the fund category. For each fund f and year t, we create a normalized average word vector across all funds managed by the investment company of f and all funds in the same fund category of fund f respectively:

$$\mathbf{d}^n_{company,f,t} = \frac{1}{F} \sum_{f' \in \text{ company of } f} \mathbf{d}^n_{f',t} \tag{3.4}$$

and

$$\mathbf{d}^n_{cat,f,t} = \frac{1}{F} \sum_{f' \in \text{ category of } f} \mathbf{d}^n_{f',t}, \tag{3.5}$$

where $\mathbf{d}^n_{f,t}$ is the normalized word vector of fund f in year t, i.e., $\mathbf{d}_{f,t}$ normalized by the sum of its elements, and F is the total number of funds in the respective investment company or fund category.[69] Then, we run the following first stage regression (without an intercept) for each fund-year observation separately:

$$\mathbf{d}^n_{f,t} = \alpha_{company,f,t}\mathbf{d}^n_{company,f,t} + \alpha_{cat,f,t}\mathbf{d}^n_{cat,f,t} + \epsilon_{f,t}, \tag{3.6}$$

where one word corresponds to one observation in the regression. Using the estimates from Equation 3.6, we compute a fund's standard content as:

$$\alpha_{standard,f,t} = \alpha_{company,f,t} + \alpha_{cat,f,t}. \tag{3.7}$$

This gives us a quantitative interpretation of how much a fund's disclosure relies on the textual information provided by funds from the same investment company and fund category. The informative, fund-specific, content is the sum of the absolute value of the residuals from Equation 3.6, i.e., $|\epsilon_{f,t}|$. The informative score, therefore, tells us how much of a fund's disclosure is not explained at the investment company and fund category level.

[69] Even though our analysis focuses on active U.S. equity funds only, we compute a fund's informative and standard score by relating a fund's textual content to *all* funds managed by its investment company. This is an important condition since otherwise, we would lose a large part of the variation at the investment company level.

We estimate informative and standard scores for each section in funds' prospectuses and for all sections together.

One might intuitively think that a more informative disclosure automatically implies a less standard disclosure. However, in line with Hanley and Hoberg (2010), we find that the Pearson correlation between funds' informative and standard scores is -0.28 (p-value < 0.01). This suggests that a higher informative score does not automatically correspond to a lower standard score. Following Hanley and Hoberg (2010) we make sure that we do not employ such a mechanistic relation by taking the sum of the absolute values of the residuals from Equation 3.6. Table 3.5 shows the summary statistics per section and year for our sample of active U.S. equity funds. Unsurprisingly, our results are even more distinct when looking at the complete universe of funds.

The results in Panel D of Table 3.5 indicate that the informative coefficient for our sample decreases continually over time while the standard coefficient increases. This effect is most pronounced for the risk statement section, see Panel A, and dominates the effect for the complete prospectus (Panel D). Already Figure 3.1 has shown that the length in funds' qualitative risk disclosures is increasing over time. Therefore, these two observations together suggest that, on average, adding information to risk statements does not automatically increase the informativeness of risk disclosures but rather implies a stronger standardized character of these statements. We do not find a comparable effect for the strategy and primary objective sections regarding changes in the coefficients over time. This finding is reasonable as changes in these two sections are less frequent than in the risk statement section. Funds' strategy statements (Panel B) and primary objectives (Panel C) are relatively persistent over time regarding their informative and standard scores.

3.3.5 Disclosure Updates

Our measure of informative and standard content focuses on cross-sectional differences in funds' qualitative disclosures. However, regulators, as well as recent academic research, have pointed out the importance of timely updates of firms' disclosures in general (e.g., Brown and Tucker, 2011; Cohen et al., 2020). As funds provide yearly snapshots of their prospectuses, we can gauge the informativeness of a fund's disclosure over time by exploiting within fund variation. Updating a textual disclosure means that the investment company adds or removes statements from one year to the next in the respective section of a fund's prospectus.

Table 3.5: **Summary statistics disclosure informativeness**

Table 3.5 shows summary statistics, i.e., mean and standard deviation (Std), of the respective summary sections (Panel A, B, and C) and of the complete summary section (Panel D) in funds' prospectuses for both the standard and the informative coefficient obtained from estimating Equation 3.6. Table 3.5 displays the results for active U.S. equity funds, while we estimate Equation 3.6 using the complete set of funds to capture all variation of funds at the investment company level.

Panel A: Risk statement

	Standard		Informative		
Year	Mean	Std	Mean	Std	N
2011	0.85	0.23	1.07	0.16	1,382
2012	0.92	0.16	1.05	0.16	1,214
2013	0.92	0.16	1.04	0.16	1,195
2014	0.92	0.16	1.04	0.17	1,152
2015	0.92	0.16	1.03	0.17	1,215
2016	0.93	0.16	1.02	0.16	1,247
2017	0.94	0.15	1.01	0.17	1,318
2018	0.93	0.16	1.01	0.18	1,355

Panel B: Strategy statement

2011	0.92	0.22	1.19	0.15	1,382
2012	0.91	0.23	1.20	0.16	1,214
2013	0.91	0.25	1.20	0.17	1,195
2014	0.91	0.26	1.19	0.17	1,152
2015	0.91	0.25	1.19	0.17	1,215
2016	0.91	0.24	1.19	0.17	1,247
2017	0.91	0.24	1.19	0.17	1,318
2018	0.91	0.24	1.19	0.16	1,355

Panel C: Primary objective

2011	0.99	0.34	1.10	0.26	1,382
2012	1.00	0.34	1.10	0.27	1,214
2013	0.99	0.35	1.11	0.26	1,195
2014	0.98	0.34	1.14	0.26	1,152
2015	0.97	0.32	1.14	0.25	1,215
2016	0.99	0.33	1.14	0.26	1,247
2017	1.00	0.34	1.14	0.26	1,318
2018	0.99	0.33	1.13	0.25	1,355

Panel D: All sections

2011	0.82	0.22	1.04	0.14	1,382
2012	0.87	0.17	1.01	0.13	1,214
2013	0.87	0.17	1.01	0.13	1,195
2014	0.87	0.17	1.00	0.14	1,152
2015	0.87	0.17	1.00	0.14	1,215
2016	0.87	0.16	0.99	0.14	1,247
2017	0.88	0.16	0.98	0.15	1,318
2018	0.88	0.16	0.98	0.15	1,355

To create our update measure, we compute how similar a fund's disclosure in year t is relative to its disclosure in the previous year $t-1$. We employ again the cosine similarity in Equation 3.3 using tf-idf weights to quantify a fund's update changes. More specifically, we calculate the $\text{Update}_{f,t}$ variable (in %) between the disclosure of a fund f for two consecutive years t and $t-1$ as

$$\text{Update}_{f,t} = \left(1 - \frac{\vec{V}(\mathbf{d}_{f,t})\vec{V}(\mathbf{d}_{f,t-1})}{||\vec{V}(\mathbf{d}_{f,t})||_2||\vec{V}(\mathbf{d}_{f,t-1})||_2}\right) \times 100. \tag{3.8}$$

The *Update* score is 0 (100) when a fund's disclosures in two successive years are identical (completely orthogonal to each other).

Table 3.6 shows the summary statistics for the update variable, based on Equation 3.8, for all three sections individually (Panel A–C) and aggregated (Panel D) over time.

Regarding updates in all three sections together (Panel D in Table 3.6), we find updates on average of about 3.66% of the textual disclosure with a slightly decreasing trend over time. In 2012, fund prospectuses were updated by about 4.11%, while in 2018, they were updated by around 3.06%. This updating behavior is mainly driven by the risk statements (5.74% in 2012) and by the strategy statements (4.93% in 2012). The content in funds' primary objectives is rather unchanged over time, which we also observe in Panel C of Figure 3.1 regarding changes in the length of this section. Unsurprisingly, the disclosed information in the summary section of mutual fund prospectuses is rather sticky. We often observe that in some years, there are no changes at all for many funds. Nevertheless, investors can learn valuable information from these updates that funds provide in summary sections of their yearly prospectuses. We will later provide some indicative results when using this update variable to understand managerial behavior better and provide convincing intuition for our findings.

3.4 Effects of Funds' Disclosure Informativeness

While the previous Section has introduced our measure of informativeness, we now examine the relation of a fund's relative degree of informative and standard content with funds managerial behavior and investors' reactions. In particular, we explore the effects on funds' risk-taking behavior, on funds' performance, as well as on funds' flows and their corresponding implications. Additionally, we examine the value of the updated information regarding funds' risk-taking and funds' performance.

Table 3.6: **Textual similarities of qualitative disclosures**

Table 3.6 shows summary statistics (mean, the 1% percentile (p1), first quartile (p25), median, third quartile (p75), the 99% percentile (p99), and the number of observations (N)) on the the update score (in %) from year $t-1$ to t using Equation 3.3 of funds' qualitative disclosure in the summary section of their prospectus for our sample of active U.S. equity funds. The complete prospectus (All sections in Panel D) includes the union of the qualitative disclosure in a fund's risk statement (Panel A), strategy statement (Panel B), and primary objective (Panel C).

Year	Mean	p1	p25	Median	p75	p99	N
Panel A: Risk statement							
2012	5.74	0.0	0.0	1.38	7.24	45.75	1,074
2013	5.61	0.0	0.34	2.21	7.57	38.93	1,173
2014	5.00	0.0	0.0	1.28	5.68	37.13	1,140
2015	4.39	0.0	0.0	1.28	5.93	29.73	1,185
2016	5.20	0.0	0.0	1.66	7.22	36.56	1,224
2017	4.79	0.0	0.0	1.88	6.73	31.71	1,283
2018	3.54	0.0	0.0	0.77	3.70	27.34	1,331
Panel B: Strategy statement							
2012	4.93	0.0	0.0	0.94	5.35	55.97	1,074
2013	4.68	0.0	0.0	0.75	3.93	56.25	1,173
2014	4.52	0.0	0.0	0.67	3.78	55.56	1,140
2015	3.92	0.0	0.0	0.35	2.88	58.28	1,185
2016	3.97	0.0	0.0	0.16	3.24	51.98	1,224
2017	3.62	0.0	0.0	0.25	2.52	52.38	1,283
2018	3.84	0.0	0.0	0.26	2.99	54.00	1,331
Panel C: Primary objective							
2012	1.97	0.0	0.0	0.0	0.0	53.45	1,074
2013	3.05	0.0	0.0	0.0	0.0	63.59	1,173
2014	2.14	0.0	0.0	0.0	0.0	60.96	1,140
2015	1.80	0.0	0.0	0.0	0.0	56.13	1,185
2016	1.55	0.0	0.0	0.0	0.0	47.36	1,224
2017	1.42	0.0	0.0	0.0	0.0	56.22	1,283
2018	2.34	0.0	0.0	0.0	0.0	65.22	1,331
Panel D: All sections							
2012	4.11	0.0	0.22	1.59	5.10	35.11	1,074
2013	4.05	0.0	0.38	1.54	4.85	34.63	1,173
2014	3.60	0.0	0.21	1.20	4.26	34.23	1,140
2015	3.42	0.0	0.08	1.20	4.10	39.85	1,185
2016	3.82	0.0	0.10	1.37	4.35	34.91	1,224
2017	3.55	0.0	0.10	1.35	4.06	28.93	1,283
2018	3.06	0.0	0.10	0.97	3.32	30.74	1,331

3.4.1 Risk Disclosure and Fund's Risk-taking Behavior

We start by investigating whether investors learn about funds' risk-taking behavior when reading funds' summary section, especially their risk statement. In particular, we are interested in the risk profile of funds with more informative (standard) risk disclosures and whether updates in funds' risk disclosures provide informational value about their future risk-taking behavior. As proxies for managerial risk-taking behavior, we take a fund's general risk, a fund's idiosyncratic risk, and a fund's systematic risk as defined in Section 3.3.2. Additionally, we use a fund's tracking error for robustness tests, i.e., the standard deviation of a fund's returns over the last 12 months from its primary benchmark as presented in its prospectus.

In a first analysis, we relate a fund's risk-taking to the informative and standard scores of its yearly risk disclosures controlling for the same fund variables as in Section 3.3.2 using fund-year observations. We are primarily interested in the cross-sectional effects of risk disclosure informativeness on funds' risk. To uncover this effect, we concentrate on variation across funds within time and within an investment category by using year fixed effects and fund category fixed effects.[70] For our regressions, we again double-cluster standard errors at the fund and year level. Table 3.7 shows the results of our regressions.

In general, we find a positive relation between a fund's disclosure informativeness and its risk. Specifications (1)–(3) of Table 3.7 show a positive (negative) and significant relation between a fund's informativeness (standard) score and its general risk, its systematic risk, and its idiosyncratic risk.[71] Therefore, the results suggest that funds with more informative (more standard) risk disclosures exhibit a higher (lower) risk-taking behavior. Additionally, as a robustness test, we relate in specification (4) a fund's tracking error to its informative and standard scores. Confirming our findings in specification (3), we observe a positive and significant relation between a fund's tracking error and its informativeness score. Larger deviations from a fund's benchmark imply a relative increase in the fund's idiosyncratic risk and consequently materialize in a higher tracking error. The interpretation of these results from an investors' perspective indicates that funds exposed to higher risks provide investors with more informative disclosures on the risks taken. Thus, we find that riskier funds do not only provide longer risk statements (see Section

[70] Note, in all regressions below, we do not add investment company fixed effects. The reason for that is that we want to keep variation between investment companies and not only variation within investment companies for the cross-sectional analysis. Nevertheless, investment company variation is already partly included due to the way we define our informativeness scores.

[71] The effect of a fund's standard score on its idiosyncratic risk is negative but insignificant.

Table 3.7: **Risk disclosure and fund risk in the cross-section**

Table 3.7 shows in specifications (1)–(3) the coefficients of an OLS regressions at the fund-year level to analyze the effect of funds' informative and standard scores of funds' risk statements controlling for several fund characteristics. The dependent variable is the general *Fund Risk* (standard deviation of fund returns in the last 36 months), the fund's *Systematic Risk* (the market beta from estimating a 4-factor Carhart (1997) using fund returns in the last 36 months), and the fund's *Idiosyncratic Risk* (standard deviation of the residuals from estimating a 4-factor Carhart (1997) using fund returns in the last 36 months). Specification (4) shows the results of a robustness test with *Tracking Error* (standard deviation of fund returns and its primary benchmark in the last 12 months) as dependent variable. All control variables are defined in detail in Table 3.15 in the Appendix. Period of interest is 2011–2018. Standard errors are reported in parentheses and are double-clustered at the fund and year level. * , **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable	Fund Risk (1)	Systematic Risk (2)	Idiosyncratic Risk (3)	Tracking Error (4)
$\text{Informative}_{Risk}$	1.026***	0.240***	0.197***	0.239***
	(0.262)	(0.060)	(0.060)	(0.080)
Standard_{Risk}	−0.414***	−0.080**	-0.004	0.024
	(0.141)	(0.034)	(0.038)	(0.051)
Fund Flow Period	−0.004***	−0.001***	−0.001**	−0.001***
	(0.001)	(0.0002)	(0.0004)	(0.0005)
Raw Return	0.080***	0.021***	0.014**	0.019**
	(0.026)	(0.006)	(0.006)	(0.008)
log(Fund Size)	0.012	-0.002	0.015	0.024*
	(0.029)	(0.006)	(0.012)	(0.013)
log(Company Size)	−0.072***	−0.011**	−0.053***	−0.070***
	(0.021)	(0.005)	(0.008)	(0.010)
Expense Ratio	0.688**	0.138**	0.259***	0.295***
	(0.274)	(0.054)	(0.087)	(0.097)
Turnover Ratio	0.0003	-0.00003	0.001**	0.001
	(0.001)	(0.0001)	(0.0004)	(0.0005)
log(Age)	−0.136***	−0.038***	−0.041***	−0.057***
	(0.044)	(0.010)	(0.015)	(0.019)
Year FE	Y	Y	Y	Y
Category FE	Y	Y	Y	Y
Observations	8,979	8,979	8,979	8,848
R^2	0.467	0.415	0.393	0.368

3.3.2) but also that more informative risk disclosures relate to higher risk-taking.

Second, we look at risk disclosures and funds' future risk-taking. Prior literature shows that fund managers change the fund's risk-taking levels over time (e.g., Huang et al., 2011). Accordingly, we hypothesize that investors could infer information on a funds' *future* risk exposure from updates in funds' risk disclosures. We gauge the magnitude of funds' year-to-year updates by using the definition of fund-specific changes from Section 3.3.5. To uncover this relation, we then regress a fund's respective risk variable in year $t+1$ on a fund's $Update_{Risk}$ score and on the fund's $Update_{All}$ score in year t, see Equation 3.8. $Update_{Risk}$ ($Update_{All}$) compares the textual content of a fund's risk statement (all three statements) in two succeeding years, i.e., the amount of information the investment company added to or removed from the fund's risk statement (three statements). This identification strategy enables us to examine how updates in fund's disclosures in their prospectuses predict the fund's future risk exposure. The set of controls for these regressions is the same as in Table 3.7. However, instead of fund category fixed effects, we use fund fixed effects, as we are interested in how informative these fund-specific updates are for each fund individually. Table 3.8 shows the results for predicting the future risk-taking behavior in our sample of active U.S. equity funds between 2012 and 2018.[72] We double-cluster standard errors by fund and year.

Panel A in Table 3.8 reports the results from regressing a fund's future risk level in year $t+1$ on risk disclosure updates and controls in t. The results do not show any significant effects of the update scores of a fund's risk statement (or the complete summary section) on its future general risk, systematic risk, or idiosyncratic risk levels. Hence, looking at individual fund-specific risk variation, our results do not indicate that larger year-to-year updates are predictive of higher future risk levels for the same fund.

In a next step, we then look at changes in funds' risk. Since updates in funds' risk disclosures measure changes from year to year, we also regress disclosure updates on changes in funds' risk-taking behavior. Specifically, we calculate the change in risk levels for fund f as the log difference in a fund's risk in year $t+1$ relative to year t:

$$\Delta \text{risk}_{f,t+1} = \log\left(\frac{\text{risk}_{f,t+1}}{\text{risk}_{f,t}}\right). \tag{3.9}$$

We do this for the raw change as well as for the absolute change $|\Delta \text{risk}_{f,t+1}|$. Taking absolute values allows us to study the magnitude of changes independent of the direction

[72]Since we calculate the difference between two qualitative disclosures over time, we do not have an independent variable for 2011 as our prospectus data sample starts in 2011.

Table 3.8: **Risk disclosure updates and future managerial risk-taking**

Table 3.8 shows the coefficients of OLS regressions with future fund's risk as the dependent variable. Panel A reports coefficients estimates from OLS regressions with risk levels in year $t+1$ as dependent variable and $Update_{Risk}$ and $Update_{All}$ as main regressors of interest. Panel B reports coefficients estimates from OLS regressions with the absolute changes in the respective risk variable (*risk*) from year $t+1$ relative to the previous year t as dependent variable. Panel C reports coefficients estimates from OLS regressions with the changes in the respective risk variable (*risk*) from year $t+1$ relative to the previous year t as dependent variable, i.e., $\Delta \text{Risk}_{f,t+1} = \log(\text{risk}_{f,t+1}/\text{risk}_{f,t})$. The independent variables of interest, Update_{Risk} and Update_{All}, measure the update in a fund's textual risk statement and the complete summary section from year t relative to the previous year $t-1$ (see Equation 3.8). The set of controls is in Panel A, B, and C the same i.e., *log(Fund Size), log(Company Size), Expense Ratio, Turnover Ratio, log(Age), Flow Period, Return Period, log(# of words)*. All control variables are measured in year t and defined in detail in Table 3.15. Period of interest is 2012–2018. Standard errors are reported in parentheses and are double-clustered at the fund and year level. * , **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Future fund risk in year $t+1$

Dependent variable	Fund Risk_{t+1}	Syst. Risk_{t+1}	Idio. Risk_{t+1}	Fund Risk_{t+1}	Syst. Risk_{t+1}	Idio. Risk_{t+1}
	(1)	(2)	(3)	(4)	(5)	(6)
Update_{Risk}	-0.020	-0.021	0.001			
	(0.075)	(0.021)	(0.028)			
Update_{All}				0.007	-0.024	0.036
				(0.107)	(0.027)	(0.049)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
Observations	6,144	6,144	6,144	6,144	6,144	6,144
R^2	0.968	0.973	0.944	0.968	0.973	0.944

Table 3.8 continued.

Panel B: Absolute changes in fund risk in year $t+1$ relative to year t

Dependent variable	$\|\Delta$ Fund Risk$\|$	$\|\Delta$ Syst. Risk$\|$	$\|\Delta$ Idio. Risk$\|$	$\|\Delta$ Fund Risk$\|$	$\|\Delta$ Syst. Risk$\|$	$\|\Delta$ Idio. Risk$\|$
	(1)	(2)	(3)	(4)	(5)	(6)
Update_{Risk}	0.014	-0.011	0.025			
	(0.011)	(0.024)	(0.031)			
Update_{All}				0.027**	-0.007	0.024
				(0.013)	(0.028)	(0.038)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
Observations	6,144	6,144	6,144	6,144	6,144	6,144
R^2	0.524	0.544	0.290	0.524	0.544	0.290

Panel C: Changes in fund risk in year $t+1$ relative to year t

Dependent variable	Δ Fund Risk	Δ Syst. Risk	Δ Idio. Risk	Δ Fund Risk	Δ Syst. Risk	Δ Idio. Risk
	(1)	(2)	(3)	(4)	(5)	(6)
Update_{Risk}	-0.026	−0.053**	-0.054			
	(0.023)	(0.021)	(0.055)			
Update_{All}				−0.041*	−0.084***	-0.081
				(0.024)	(0.032)	(0.065)
Update_{Risk}	-0.020	-0.021	0.001			
	(0.075)	(0.021)	(0.028)			
Update_{All}				0.007	-0.024	0.036
				(0.107)	(0.027)	(0.049)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
Observations	6,144	6,144	6,144	6,144	6,144	6,144
R^2	0.712	0.443	0.263	0.712	0.443	0.263

of changes in risk levels. This is also relevant from an investor's perspective since the direction of changes is probably more difficult to discover by reading a fund's disclosure than measuring the absolute magnitude of a fund-specific update.

Panel B in Table 3.8 shows that updates in funds' summary sections have a positive and significant effect on future absolute changes in a fund's risk-taking behavior in terms of its general risk (specification (4)). For a fund's idiosyncratic risk, we find a positive but insignificant effect (specifications (3) and (6)). Finally, in Panel C of Table 3.8 we look at directional changes in a fund's future risk levels. For all risk changes, we find a negative effect of updates in both a fund's risk statement separately and the complete summary section on future risk-taking. This effect is statistically significant for a fund's general and systematic risk in specifications (2), (4), and (5). Thus, the negative relation suggests that funds providing larger disclosure updates in their prospectuses reduce more strongly their risk-taking in the future.

3.4.2 Qualitative Disclosures and Fund Performance

Our results so far indicate a positive relationship between the informativeness of funds' risk disclosures and levels of risk-taking, while risk disclosure updates are predictive of future changes in funds' risk-taking behavior. However, it remains unclear how a fund's disclosure informativeness relates to a fund's performance. As a fund's risk-taking increases (decreases) in its informativeness (standard score), we expect in line with the traditional risk-return trade-off in finance that a fund's performance is increasing in its informativeness as well. Hence, we examine the effect of disclosures on raw returns and, in particular, funds' risk-adjusted performance. From an investor's perspective, we answer whether investing in funds with more informative and less standard disclosures is actually rewarding in terms of fund performance. Finally, we look again at the relation of fund-specific updates of funds' disclosure content from one year to the next and its predictability of funds' future performance.

We start by relating a fund's informative scores and standard scores to its contemporaneous performance using fund-year observations. For the risk-adjusted return measures, we compute a fund's alphas, i.e., the CAPM alpha, the Fama and French (1993) 3-factor alpha, and the Carhart (1997) 4-factor alpha, for our sample of active U.S. equity funds. To estimate funds' alphas, we use funds' as well as stock market factors' daily returns for each calendar year.[73] Fund age, fund size, company size, expense ratio, turnover, and

[73]We thank Kenneth French for providing data on stock market factors, available at

fund flows are our set of control variables. We include year fixed effects as well as fund category fixed effects, and again double-clustered standard errors at the fund and year level. Finally, we use the estimated alphas as dependent variables for our panel regressions and regress it on the fund's informative and standard scores and the set of fund characteristics. Table 3.9 shows the results for the different sections in the summary prospectus. We only show the results for the 4-factor alpha, as our results are robust when using raw returns, or the CAPM alpha, or the 3-factor alpha (see Table 3.14 in the Appendix).

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http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table 3.9: **Disclosure informativeness and fund performance in the cross-section**

Table 3.9 shows the coefficients of OLS regressions of fund performance of funds' informative and standard scores of different sections in their summary section of the prospectus and various fund characteristics. The dependent variable is the annualized Carhart (1997) 4-factor alpha ($\hat{\alpha}$ (4FF)) in %. Alphas are computed using daily fund returns over 12 months in each calendar year. All control variables are defined in detail in Table 3.15 in the Appendix. Period of interest is 2011–2018. Standard errors are reported in parentheses and are double-clustered at the fund and year level. * , **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable			$\hat{\alpha}$ (4FF)		
	(1)	(2)	(3)	(4)	(5)
$\text{Informative}_{Risk}$	2.140***				1.829**
	(0.687)				(0.756)
Standard_{Risk}	0.408				0.492
	(0.624)				(0.585)
$\text{Informative}_{Objective}$		-0.014			
		(0.252)			
$\text{Standard}_{Objective}$		−0.542**			
		(0.236)			
$\text{Informative}_{Strategy}$			1.458***		0.499
			(0.485)		(0.510)
$\text{Standard}_{Strategy}$			-0.714		-0.314
			(0.451)		(0.448)
Informative_{All}				2.253***	
				(0.757)	
Standard_{All}				0.744	
				(0.704)	
log(Fund Size)	-0.042	-0.053	-0.042	-0.049	-0.041
	(0.093)	(0.095)	(0.093)	(0.092)	(0.092)
log (Company Size)	-0.015	0.027	-0.018	-0.009	-0.020
	(0.080)	(0.078)	(0.079)	(0.079)	(0.080)
log(Age)	0.091	0.132	0.101	0.090	0.090
	(0.230)	(0.239)	(0.236)	(0.236)	(0.232)
Expense Ratio	0.037	0.061	0.037	0.032	0.034
	(0.238)	(0.238)	(0.236)	(0.236)	(0.237)
Turnover Ratio	−0.010***	−0.010***	−0.010***	−0.010***	−0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Fund Flow Period	0.087***	0.087***	0.087***	0.087***	0.087***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Year FE	Y	Y	Y	Y	Y
Category FE	Y	Y	Y	Y	Y
Observations	8,972	8,972	8,972	8,972	8,972
R^2	0.254	0.252	0.252	0.253	0.254

The results in Table 3.9 show a highly significant and positive effect of informativeness – in the risk statement, strategy statement, and the complete summary section – on a fund's performance. The more informative these sections are, the higher the fund's alphas in the same year. Contrarily, we find a statistically non-significant effect of standard scores or for the standard score of the investment objective section even a statistically significant negative effect (at the 5% level). The remaining coefficients of informative and standard scores are insignificant. These findings indicate that funds with more informative (standard) disclosures also achieve relatively higher (lower) factor-adjusted returns.[74] Therefore, the informativeness of funds' summary sections can be used as a selection criterion to identify contemporaneously better performing funds.

One might argue that our overall finding here is due to the unique investment styles of some funds described in their strategy narrative (Kostovetsky and Warner, 2020). We test for this by including in specification (5) the informative and standard scores for both the risk statements and the strategy statements. The correlation between risk and strategy informativeness in our sample is 0.44 (p-value < 0.01). The results of specification (5) show that a fund's risk informativeness has additional value on top of its strategy informativeness when looking at contemporaneous fund performance. The coefficient of the informative risk variable is still statistically significant (p-value < 0.05), though smaller in magnitude.

Next, having explored the informativeness of funds' qualitative disclosures in their summary sections and funds' performance in the cross-section, we study disclosure updates over time and how informative these updates are to investors. Updates might be important signals to investors about the future performance of a fund (Brown and Tucker, 2011; Cohen et al., 2020). Therefore, to analyze the relation between fund performance and disclosure updates, we predict yearly performance measures for all active U.S. equity funds between 2012 and 2018. Again, we use fund fixed effects and year fixed effects and double-clustered standard errors at the fund and year dimensions. Table 3.10 shows the results for each summary section, respectively.

Specifications (3) and (4) in Table 3.10 report a statistically significant and positive relation between fund's future performance and content-based updates of a fund's strategy statement as well as updates of the complete summary section. We also find a positive coefficient for the update of a fund's risk statement (significant at the 10% level in specification (1)), while the sign of the coefficient of primary objective updates in specification (2) is negative and significant at the 5% level. We do not stress the finding of the updated primary objective too much, as it constitutes only a small fraction of a fund's prospectus (see Figure 3.1), and only a very small proportion of funds provides an update of this section (less than 75% of all funds update this information (see Panel C of Table 3.6)).

[74] We find a similar but less significant relation for the strategy section in unreported results when taking funds' raw returns instead of 4-factor alphas as the dependent variable.

Table 3.10: **Disclosure updates and future fund performance**

Table 3.10 shows the coefficients of OLS regressions with fund performance on year-to-year updates in different sections in their summary section of the prospectuses and various fund characteristics. The dependent variable is the annualized Carhart (1997) 4-factor alpha in the next year ($\hat{\alpha}$ $(4FF)_{t+1}$) in %. Alphas are computed using daily fund returns over 12 months in each calendar year. The *Update* variable (in %) is defined between 0 and 100 (see Equation 3.8). All control variables are defined in detail in Table 3.15 in the Appendix. Specification (1) shows the results for updates in funds' risk statements, specification (2) for updates in the objective statements, specification (3) for the strategy statements, and specification (4) for the complete summary section. Period of interest is 2012–2018. Standard errors are reported in parentheses and are double-clustered at the fund and year level. * , **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable	$\hat{\alpha}$ $(4FF)_{t+1}$			
	(1)	(2)	(3)	(4)
Update_{Risk}	2.695*			
	(1.408)			
$\text{Update}_{Objective}$		−1.633**		
		(0.745)		
$\text{Update}_{Strategy}$			2.193***	
			(0.467)	
Update_{All}				3.571***
				(0.970)
Flow Period	0.010	0.010	0.010	0.010
	(0.007)	(0.007)	(0.007)	(0.007)
log(Fund Size)	−1.582**	−1.602**	−1.609**	−1.580**
	(0.712)	(0.708)	(0.691)	(0.711)
log(Company Size)	-0.524	-0.542	-0.519	-0.513
	(0.359)	(0.359)	(0.387)	(0.363)
Expense Ratio	1.170*	1.159*	1.176**	1.158*
	(0.617)	(0.615)	(0.591)	(0.612)
Turnover Ratio	0.006	0.006	0.006	0.006
	(0.005)	(0.005)	(0.005)	(0.005)
log(Age)	1.006	1.012	0.969	0.989
	(0.928)	(0.931)	(0.971)	(0.937)
Year FE	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y
Observations	6,144	6,144	6,144	6,144
R^2	0.495	0.495	0.495	0.495

Our results suggest that updates of funds' textual disclosures have explanatory power for funds' future performance. For example, if a fund's content changes by 4% (the mean value in our sample), a fund's alpha increases by approximately 14 basis points in the next year.[75]

Accordingly, investors could use updates in funds' qualitative statements as a source of information when making an investment decision. First, investors can interpret funds' updates of their strategy disclosures as a positive signal for the fund's future performance. More extensive adjustments of the investment strategy in funds' prospectuses relate to higher future performance. This positive relation could serve as a proxy for fund governance. In particular, better governed funds might provide more accurate information on their investment strategy, and this information is updated in a timely manner. For instance, we know from the literature that funds with better, i.e., more independent, board governance achieve higher returns and charge lower fees (Tufano and Sevick, 1997; Ding and Wermers, 2012). Second, updates in funds' strategy statements might signal investors that a fund indeed makes adjustments to its investment strategy, and this adjustment is profitable for investors in terms of next years' risk-adjusted fund performance.

3.4.3 Informativeness and Fund Flows

It remains to investigate investors' reaction to informative and standard components of the qualitative content in funds' prospectuses. More precisely, we examine whether more informative (more standard) prospectuses of funds experience relatively higher (lower) fund flows. We predict that the more informative a fund's disclosure is, the easier and less costly an investor can process the qualitative information available. Our hypothesis is in line with the positive relation of fund returns and fund flows well documented by, e.g., Chevalier and Ellison (1997) as well as Sirri and Tufano (1998). Since we find in Section 3.4.2 that there is a positive relation between funds' performance and their informativeness, we also would expect that there is such a positive relation between fund flows and informativeness.

Table 3.11 shows the results for this analysis controlling for different measures of past fund performance. Specification (1) uses past yearly fund returns as a performance control. Specification (2) uses the fund's percentage rank of its raw returns in its category from the previous year and the squared rank (Sirri and Tufano, 1998). Specification (3)

[75]Note that this relation is obviously not always linear. For instance, we find a negative relation for funds that update more than 20% of their content from one year to another year.

Table 3.11: **Informativeness and fund flows in the cross-section**

Table 3.11 shows the coefficients of OLS regressions with fund flows on funds' informativeness scores and standard scores of all three sections from funds' yearly prospectuses and various fund characteristics. The dependent variable is yearly fund flows in percent (*Fund Flow Period*) as defined in Equation 3.1. Specifications (1)–(3) differ regarding the return controls they include. Specification (1) controls for a fund's yearly raw returns. Specification (2) uses a fund's yearly percent rank regarding yearly raw returns in its category (*Rank*) and the square of it as performance controls (Sirri and Tufano, 1998). Specification (3) uses quintiles of the rank as performance controls. All control variables are defined in detail in Table 3.15 in the Appendix. Period of interest is 2011–2018. Standard errors are reported in parentheses and are double-clustered at the fund and year level. * , **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable	Fund Flow Period		
	(1)	(2)	(3)
Informative_{All}	5.266*	4.273	4.534
	(3.035)	(2.974)	(2.975)
Standard_{All}	-0.295	-0.541	-0.328
	(2.348)	(2.379)	(2.412)
Summary Prospectus	2.700**	2.892**	2.924**
	(1.208)	(1.227)	(1.228)
log(Fund Size)	1.526***	1.508***	1.522***
	(0.460)	(0.464)	(0.475)
log(Company Size)	−0.743**	−0.763**	−0.777**
	(0.352)	(0.331)	(0.332)
log(Age)	−11.422***	−11.167***	−11.155***
	(0.707)	(0.716)	(0.718)
Expense Ratio	0.830	0.875	0.937
	(0.645)	(0.653)	(0.639)
Raw Return_{t-1}	0.419**		
	(0.203)		
Rank_{t-1}		6.189	
		(7.782)	
Rank^2_{t-1}		12.364**	
		(5.860)	
Bottom			19.693
			(13.665)
Mid			13.792***
			(3.694)
Top			50.698***
			(9.180)
Risk	−3.279***	−4.362***	−4.276***
	(0.955)	(1.039)	(1.070)
Year FE	Y	Y	Y
Category FE	Y	Y	Y
Observations	8,889	8,889	8,889
R^2	0.135	0.151	0.152

uses quintiles of the rank return variable from specification (2) as alternative performance control (as in Sirri and Tufano, 1998).

Indeed, in line with Sirri and Tufano (1998), funds with more informative disclosures are able to attract higher fund flows – controlling for quantitative determinants of fund flows, year fixed effects, and fund category fixed effects. In all specifications of Table 3.11, we find that fund flows increase in funds' informativeness and decrease in funds' standard scores. The respective signs of the coefficients are in line with our theoretical expectations. However, our results do not show an overwhelming statistical significance, which indicates that investors react only to some extent to the informativeness in funds' disclosure content. Unsurprisingly, it is rather challenging for investors to identify the degree of informativeness of mutual fund prospectuses, but investors are, at least to some extent, able to differentiate between informative and standard content in fund prospectuses.

In addition to the common controls for fund flows, e.g., fund size or age, we also add a summary prospectus dummy variable to the regressions. As we outlined in Section 3.2, funds might voluntarily provide an additional summary prospectus, which contains the same content as the summary section in the statutory prospectus. In line with the academic literature (e.g., Brown et al., 2008), we find support for the information disclosure hypothesis. Namely that funds are rewarded for voluntarily disclosing additional information. The coefficient of the summary prospectus dummy is positive and statistically significant at the 5% level across all specifications of Table 3.11. Regarding the magnitude of the coefficients, we document that if a fund provides investors with a summary prospectus, its yearly fund flows are on average at least 2.7 percentage points higher compared to not releasing a summary prospectus.

3.5 Conclusion

This paper examines the informational value of qualitative disclosures of U.S. mutual funds prospectuses and their relation to funds' risk-taking, funds' performance, and investors' reaction. We use methods from textual analysis to investigate in more detail a sample of active U.S. equity funds between 2011 and 2018 that report their principal risks, strategy narratives, and investment objectives in the summary section of their yearly updated full prospectuses.

First, we document significant heterogeneity in the amount of risk disclosure across funds. A large proportion of the cross-sectional variation can be explained by unobserved heterogeneity at the investment company level and a smaller part by a fund's category. We find similar results when examining the actual written content of funds' disclosures. Accordingly, we introduce an informativeness measure of a fund's disclosure related to i) all other funds by the same investment company and ii) all other funds in the same category. In this setting, we identify a fund's disclosure as relatively standard if a company provides the same risk disclosures for all the funds it manages and the funds' disclosures do not contain any fund-specific information.

Second, we examine the implications of funds' levels of informative and standard disclosures for funds' risk-taking behavior, funds' performance, and funds' flows. Our results show that funds with more informative risk disclosures take higher risks, and that updates in funds' risk disclosures are predictive of changes in funds' future risk-taking. Moreover, we show that funds' risk-adjusted performance increases with their disclosure informativeness. This effect is not driven by the uniqueness of funds' strategy statements but is due to the information in funds' risk disclosures. Regarding content-based updates of funds, we document that updates of funds' qualitative strategy disclosures positively and significantly predict future fund performance. Finally, looking at investors' reactions via fund flows, we find only weak evidence that investors respond to the informative and standard content in funds' prospectuses.

Overall, our findings suggest that funds' qualitative disclosures in their prospectuses are informative to investors. However, there is considerable heterogeneity in the cross-section of funds determined mainly at the investment company dimension, and which impedes for investors a simple comparison of different funds.

A.3 Example Same Risk Section

Example for a risk statement that is used for two different funds from the same investment company. The excerpts are from The Torray Fund and The Torray Resolute Fund for 2013).[76]

Principal Risks of Investing in the Fund:

General Risk
All investments are subject to inherent risks, and an investment in the Fund is no exception. Accordingly, you may lose money by investing in the Fund and investors face the risk that Torray LLC's (the Manager) business analyses prove faulty.

Market Risk
The value of the Fund's investments will fluctuate as markets fluctuate and could decline over short- or long-term periods.

Focused Portfolio Risk
The Fund attempts to invest in a limited number of securities. Accordingly, the Fund may have more volatility and is considered to have more risk than a fund that invests in a greater number of securities because changes in the value of a single security may have a more significant effect, either negative or positive, on the Fund's net asset value (NAV). To the extent the Fund invests its assets in fewer securities, the Fund is subject to greater risk of loss if any of those securities become permanently impaired.

No Guarantee
An investment in the Fund is not a deposit of a bank and is not insured or guaranteed by the Federal Deposit Insurance Corporation or any other government agency.

[76] The original filing for the fund's summary section is available at https://www.sec.gov/Archives/edgar/data/862696/000119312513216290/0001193125-13-216290.txt.

B.3 Example Strategy Statement Change

Example for an updated strategy statement. The excerpts are for the same fund from 2013 and 2014.

2013

Principal Investment Strategy:[77] The Fund's strategy is to invest in high quality companies that have a record of increasing sales and earnings, and to hold them as long as their fundamentals remain intact. Capable management and sound finances are critical considerations in the selection process. Ordinarily, 90% or more of the Fund's assets will be invested in common stocks, preferred stocks, and securities convertible into common stocks with the balance held in fixed-income securities, U.S. Treasury securities or other cash equivalents. The Fund usually holds between 25 and 40 stocks. Positions in individual issuers will generally not exceed 8% of assets and positions in industry groupings will generally not exceed 25% of assets. Investments are made when it is believed that a company's long-term outlook is sound and the shares are fairly priced

2014

Principal Investment Strategy:[78] The Fund invests in the common stocks of high quality businesses that are fairly priced and run by sound management. These companies must have solid finances and a long-term record of rising sales, earnings and free cash flow. Investments are held as long as the issuers' fundamentals remain intact. The Fund invests principally in the common stocks of large capitalization companies. Large capitalization companies are those with market capitalizations of $8 billion or more. 90% or more of the Fund's assets will be invested in common stocks with the balance held in U.S. Treasury securities or other cash equivalents. Although the number of holdings may vary, the Fund usually holds between 25 and 40 stocks, with positions in individual issuers generally limited to between 2% and 4% of the Fund's assets. Generally, positions in individual issuers will not exceed 5% of Fund assets. The Fund will not invest in excess of 25% of its assets in any one industry and generally does not invest greater than 25% of its assets in any specific group of industries.

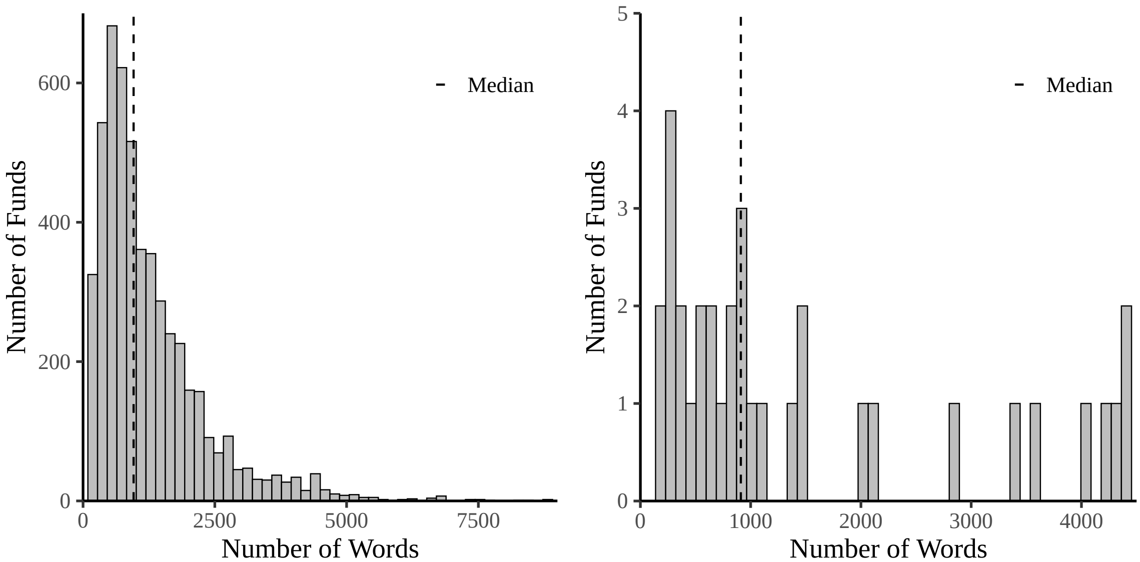
[77] The original filing for the fund's summary section is available at https://www.sec.gov/Archives/edgar/data/862696/000119312513216290/0001193125-13-216290.txt.

[78] The original filing for the fund's summary section is available at https://www.sec.gov/Archives/edgar/data/862696/000119312514198604/0001193125-14-198604.txt.

C.3 Additional Figures and Tables

Figure 3.3: **Topics in funds' risk statements in 2018**

Figure 3.3 shows the computed 25 topics using the Latent Dirichlet Allocation (LDA) model from Blei, Ng, and Jordan (2003). Words included in each word cloud are those ten words with the highest weight in the respective topic. We decided in favor of 25 topics as this number minimizes the perplexity score, i.e., the transformed mean per-word likelihood, when the fitted model is evaluated with an unseen hold-out sample. LDA is a statistical method that addresses this problem by identifying an optimal set of topics, based on word co-occurrences, that generates documents that are closest to the observed documents.



(a) **Panel A: All funds in 2018** (b) **Panel B: S&P 500 Index funds in 2018**

Figure 3.4: **Distribution of number of words in funds' risk statements in 2018**

Figure 3.4 shows the distribution of the number of words in funds' qualitative risk statements in the summary sections of their yearly prospectuses for 2018. The number of words is calculated after removing the html code from the filings. Panel A displays the distribution of number of words in risk statements of all funds in 2018. Panel B shows the distribution of words in 2018 of only S&P 500 Index funds. The vertical line marks the median length of funds' risk statements.

Table 3.12: **Data merge process**

Table 3.12 describes the process of merging and shows the final number of distinct funds and share classes in our sample. 497(K) and 485BPOS filings are available in the SEC database. Starting point is the investment companies file of the SEC with 42,057 share classes which correspond to 13,986 funds from 2010 to 2018. 40,226 of those share classes have a ticker symbol. In the Morningstar database we have 33,783 ticker symbols corresponding to 10,205 distinct funds, respectively. Merging the SEC data with the Morningstar data on Ticker and year results in 26,291 unambiguously matched share classes, respectively 8,542 funds.

Level	SEC	MS Ticker data	Merged data
Share class	42,057	33,783	26,291
	(40,226 with ticker)		
Fund level	13,986	10,205	8,542

Table 3.13: **Determinants of length of risk statements - all funds**

Table 3.13 shows the coefficients of OLS regressions with the length of a fund's risk section in its prospectus (*log(# of Words)*) as the dependent variable on various fund characteristics on all funds. *Summary Prospectus* is a dummy indicating whether the fund publishes a summary prospectus (1) or not (0). The control variables are defined in detail in Table 3.15. In the first specification (1), we regress a fund's disclosed risk on fund risk controlling for the fund category fixed effects (Category FE) and year fixed effects (Year FE). In specification (2), we add investment company fixed effects (CIK FE) to the regression. In specification (3), we alternatively control for the interaction of investment company fixed effects and year fixed effects (Year×CIK FE). The sample consists of 29,728 fund year observations between 2011 and 2018. Standard errors are reported in parentheses and are double-clustered at the fund and year level. * , **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable		$\log(\#\text{ of Words})_{Risk}$	
	(1)	(2)	(3)
Fund Risk	-0.040^{***}	0.013^{***}	0.015^{***}
	(0.012)	(0.003)	(0.003)
Fund Flow Period	-0.00003	-0.0001^{*}	-0.0001^{**}
	(0.0002)	(0.0001)	(0.0001)
Return Period	-0.003	0.001	0.0002
	(0.002)	(0.001)	(0.001)
log(Fund Size)	-0.024^{***}	0.010^{***}	0.010^{***}
	(0.005)	(0.003)	(0.003)
Expense Ratio	-0.012	-0.016	-0.018
	(0.017)	(0.011)	(0.011)
Turnover Ratio	0.0001^{**}	0.00001	0.00001
	(0.00003)	(0.00001)	(0.00001)
log(Age)	-0.127^{***}	-0.107^{***}	-0.114^{***}
	(0.014)	(0.008)	(0.008)
Summary Prospectus	-0.018	0.046^{**}	0.077^{**}
	(0.047)	(0.022)	(0.030)
Category FE	Y	Y	Y
Year FE	Y	Y	N
CIK FE	N	Y	N
Year×CIK FE	N	N	Y
Observations	29,728	29,728	29,728
R^2	0.354	0.797	0.833

Table 3.14: **Informativeness and fund performance in the cross-section**

Table 3.14 shows the coefficients of OLS regressions of fund performance of funds' informative and standard scores of the complete summary section of the prospectus and various fund characteristics. The dependent variable is the (annualized) fund's raw return, the CAPM alpha, the Fama and French (1993) 3-factor alpha, and the Carhart (1997) 4-factor alpha. Performance is measured on a yearly basis in percent. Alphas are computed using daily fund returns over the 12 months in each calendar year. All control variables are defined in detail in Table 2.16 in the Appendix. Period of interest is 2011–2018. Standard errors are reported in parentheses and are double-clustered at the fund and year level. * , **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent variable	Raw Returns	$\hat{\alpha}$ (CAPM)	$\hat{\alpha}$ (3FF)	$\hat{\alpha}$ (4FF)
	(1)	(2)	(3)	(4)
Informative_{All}	3.232*	2.144**	2.149***	2.253***
	(1.934)	(0.846)	(0.778)	(0.757)
Standard_{All}	-0.434	0.825	0.680	0.744
	(0.746)	(0.713)	(0.689)	(0.704)
log(Fund Size)	−0.116*	-0.050	-0.053	-0.049
	(0.061)	(0.096)	(0.095)	(0.092)
log(Company Size)	0.029	0.001	-0.003	-0.009
	(0.075)	(0.080)	(0.084)	(0.079)
log(Age)	-0.544	0.270	0.127	0.090
	(0.355)	(0.187)	(0.232)	(0.236)
Expense Ratio	1.132	0.059	0.049	0.032
	(0.893)	(0.243)	(0.240)	(0.236)
Turnover Ratio	−0.006***	−0.009***	−0.009***	−0.010***
	(0.002)	(0.003)	(0.003)	(0.003)
Fund Flow Period	-0.005	0.101***	0.089***	0.087***
	(0.015)	(0.017)	(0.014)	(0.013)
Year FE	Y	Y	Y	Y
Category FE	Y	Y	Y	Y
Observations	8,972	8,972	8,972	8,972
R^2	0.486	0.292	0.253	0.253

Table 15: **Variable definitions**

Table 3.15 provides definitions of all variables used in this paper. MS indicates Morningstar, C refers to own calculations by the authors, and SEC indicates data from the Securities and Exchange Commission.

Variable name	Description	Source
Fund Flow (%)	Computed as $(TNA_{f,t} - TNA_{f,t-1}(1 + RF_{f,t}))/(TNA_{f,t-1}(1 + RF_{f,t}))$, where $TNA_{f,t}$ corresponds to fund f's total net assets (TNA) in month t and $RF_{f,t}$ denotes fund f's return in month t. The variable is winsorized at the 1st and 99th percentile.	MS, C
Raw Return (%)	Percentage return calculated as the change in yearly net asset value minus management fees and other regular costs.	MS
$\hat{\alpha}$ (CAPM) (%)	Annualized performance alpha from the market model. Market returns are from the Kenneth French library. The alphas are estimated in sample using daily fund returns for the respective calendar year.	MS, C
$\hat{\alpha}$ (3FF) (%)	Annualized performance alpha from a model including the Fama and French factor returns for the market (Fama and French, 1993). Market returns are from the Kenneth French library. The alphas are estimated in sample using daily fund returns for the respective calendar year.	MS, C
$\hat{\alpha}$ (4FF) (%)	Annualized performance alpha from a model including the Fama and French factor returns for the market as well as the Carhart momentum factor (Carhart, 1997). Market returns are from the Kenneth French library. The alphas are estimated in sample using daily fund returns for the respective calendar year.	MS, C
Fund Size (in mn.)	Fund's total net assets in million USD, aggregated at the share class level.	MS
log (Fund Size)	Logarithm of fund's total net assets in million USD, aggregated at the share class level.	MS, C
log (Company Size)	Logarithm of company's total net assets in million USD, aggregated at the fund level.	MS, C
Expense Ratio (%)	A fund's annual expense ratio expressed in percent.	MS
Age (in months)	Fund's age computed as the difference from the end of the year to the inception date of the oldest share class.	MS, C
log(Age)	Logarithm of fund's age in months computed as the difference from end of the year to the inception date of the oldest share class.	MS, C
Turnover Ratio (%)	Lesser of purchases or sales (excluding all securities with maturities of less than one year) and dividing by average monthly net assets.	MS

Table 3.15 continued.

Variable name	Description	Source
Fund Risk	Standard deviation of a fund's monthly returns from the prior 36 months.	MS, C
Systematic Risk	A fund's beta measured as the slope of the regression of the monthly excess return from estimating a 4-factor Carhart (1997) model using a funds' monthly returns from the prior 36 months. For this estimate, we demand for at least 24 observations.	MS, C
Idiosyncratic Risk	A fund's risk measured as the standard deviation of the residuals from estimating a 4-factor Carhart (1997) model using a funds' monthly returns from the prior 36 months. For this estimate, we demand for at least 24 observations.	MS, C
Tracking Error	Standard deviation of a fund's return and its primary benchmark (as indicated in the prospectus) in the last 12 months.	MS
Fund Flow Period	Fund flows over the 12 months before the calendar year end.	MS, C
Summary Prospectus	Dummy whether the fund issues a summary prospectus (1) or not (0).	SEC, C
Category	Morningstar assigns each fund to 1 of 70 fund categories.	MS
CIK	Unique identifier of the investment company that issues the fund. This mapping is manually created by aggregating information on companies Central Index Key (SEC) from the SEC EDGAR website and internet search.	SEC, C
Number of Words	Number of words in the risk statements.	SEC, C
log(# of Words)	Logarithm of the number of words in the risk statements.	SEC, C
Informative	Informative score of a fund's textual disclosures (by sections in funds' prospectuses), which is the sum of the residuals of the regression defined in Equation 3.6.	C
Standard	Standard score of a fund's textual disclosures (by sections in funds' prospectuses), which is the sum of the two coefficients in Equation 3.7.	C
Update	Update is calculated as the cosine similarity between textual disclosures of a fund in two consecutive years. See Equation 3.8 for a definition.	C

Mutual Fund Names and Style (Mis-) Information

Joint with Anne-Florence Allard and Kristien Smedts[‡]

Mutual funds often inform via their name about the investment style that is pursued. We document that a significant proportion of mutual fund names provides inaccurate information, i.e., the fund's investment style does not align with the given name. Funds that deviate from the investment style suggested in their name performed worse, had lower fund inflows, took more risk, and charged higher expenses than their competitors. Evidence shows that, in particular, the tournament character of the fund industry causes fund name deviations. In addition, the risk-return trade-off deteriorates following a misnaming practice. Moreover, we document that investors experience difficulties in responding in a timely manner to this misleading name information.

4.1 Introduction

Do mutual fund names convey reliable information? In this paper, we shed light on this question by studying mutual fund names' alignment with mutual funds' *actual* investment styles.

[‡]Anne-Florence Allard, School of Accounting and Finance, University of Bristol, UK & Department of Accounting, Finance & Insurance, KU Leuven, Belgium. Email: anneflorence.allard@bristol.ac.uk; Jonathan Krakow, Department of Banking and Finance, University of Zurich, Switzerland. Email: jonathan.krakow@bf.uzh.ch; and Kristien Smedts Department of Accounting, Finance & Insurance and LRisk, KU Leuven, Belgium. Email: kristien.smedts@kuleuven.be. We are grateful for comments from Christoph Basten, Marc Chesney, Hans Degryse, Mike Gallmeyer, Thorsten Hens, Leonardo Iania, Steven Ongena, Randy Priem, Silvina Rubio, Timo Schäfer, Paul Smeets, Gertjan Verdickt, Alexander Wagner, Gunther Wuyts, and Alexandre Ziegler as well as seminar participants at the University of Bristol. Anne-Florence Allard acknowledges financial support from the Research Foundation - Flanders (FWO).

At year-end 2018, there were more than 119,000 regulated funds worldwide having more than U.S. $46 trillion in total net assets (Investment Company Institute, 2019). Investors thus face a broad menu of investment options, and to simplify the selection process, they often rely on information or heuristics summarising key fund characteristics. For instance, investors (over-)weight past performance, explicit fees, or base their decision on qualitative information such as the fund's name or its ticker symbol (see, e.g., Sirri and Tufano, 1998; Jain and Wu, 2000; Barber et al., 2005; Cooper et al., 2005; Espenlaub et al., 2017).[79]

As a result, fund managers often include salient information in the fund's name – such as the asset class, e.g., equity/bonds, or the investment style of the fund, e.g., value/growth, or small/mid/large-cap. Providing such information in the name should facilitate the selection process of investors, for sure when they are less sophisticated. However, what if fund managers do not truthfully inform—or even intentionally misinform—about the strategy in the fund's name?

In this paper, we investigate this phenomenon of inaccurate fund names. Using cluster analysis coupled with a return-based analysis, we are able to show the prevalence of inaccurate fund names, i.e., a misalignment between the fund's investment style and name. Subsequently, we aim to shed light on the reasons and consequences of inaccurate fund names. This analysis is motivated by the tournament hypothesis of Brown et al. (1996) who consider the mutual fund market as a competitive tournament in which funds with comparable investment objectives compete against each other. They show that relative winners within a fund category experience higher fund inflows relative to their competitors. Moreover, higher inflows result in higher compensation for the fund managers (Chevalier and Ellison, 1997). Therefore, in an attempt to become relative winners, mutual fund managers might decide to follow a deviating strategy. This mainly plays at year end, when the fund's performance is recorded and the compensation is determined. Based on this relationship, we expect that relative losers over the course of a year will increase their efforts to switch to the relative winners' side by the end of the year. One strategy to do so is to deviate from the investment style suggested by the fund's name

[79] Thaler (2016) provides anecdotal evidence of investors' behavior regarding a closed-end mutual fund. A fund having the ticker symbol "CUBA" and investing in the Caribbean traded historically (like most closed-end funds) at a 10 to 15% discount relative to the net assets value. However, in December 2014, when President Obama announced to relax conditions for U.S. firms to do business in Cuba, this fund experienced a significant increase in the price of more than 70% without any change in the net asset value. Thus, investors overweighted the qualitative information based on the ticker symbol and interpreted it as a relation to the country Cuba.

and change the portfolio's exposure profile. This effect is amplified due to an asymmetric return-flow relationship, where relative winners gain inflows, but relative losers do not experience outflows (see Brown et al., 1996; Chevalier and Ellison, 1997). Due to this asymmetric pattern of the flow-performance relationship and due to the tournament setting, mainly within a strategy category, managers of funds with relatively lower returns over a year thus have incentives to change the investment strategy of the fund by the end of the year. The fund name's inaccuracy therefore emerges from a principal-agent conflict, in which the fund manager aims to maximize his/her compensation.

In a second part, we analyze the consequences of improper naming practices. We study the fund's subsequent return and risk to shed light on the success of the strategy to deviate. We also analyze the investors' subsequent reaction by investigating fund in- and outflows.

Over a period spanning from 2010 up to 2018, we document that a significant fraction of U.S. equity mutual funds provides inaccurate naming information: 33% of U.S. equity mutual funds have, at least once in their life-cycle, an inaccurate name. Often, however, misnaming occurs for multiple periods over the life-cycle. In addition, we provide evidence that this phenomenon of inaccurate naming mainly results from changes in the underlying portfolio without an appropriate change in the mutual fund's name (discussed in Section 4.5).

To explore this finding further, we study which fund characteristics can be linked to this misnaming practice. We show that mutual funds, prior to their misnaming, underperform in many dimensions compared to accurately named funds. In particular, the degree of inaccuracy is higher when the fund received lower inflows, charged higher fees, and was exposed to more idiosyncratic risk. Our results also highlight the tournament hypothesis and confirm the potential principal-agent conflict (Brown et al., 1996). When funds are relative losers during the first quarters of a year, they tend to deviate more from the style suggested by their name, resulting in inaccurate fund naming.

Importantly, we document that the above strategy is on average not successful: focusing on relative performance, funds that deviate from their name-suggested strategy do not end-up being relative winners. Thus, a deviation to improve one's performance rank does not seem to be effective, on average. Moreover, while the risk-return trade-off deteriorates following a misnaming practice, investors do not reduce their investments in such funds. This finding is in line with the asymmetric relationship of returns and flows (see, e.g., Sirri and Tufano, 1998) and highlights the difficulties that investors experience in noticing such inaccurate information in a timely manner.

The importance of mutual fund names in investors' investment decisions has long been recognized by the Security and Exchange Commission (SEC). For instance, in 2001, the SEC stated that "the name of an investment company may communicate a great deal to an investor" (SEC, 2001). This recognition resulted in Rule 35d-1, introduced in July 2001, to regulate mutual fund names. Hence, to prevent misleading information in the name, the rule requires funds that mention an asset class in their name to invest at least 80% of the portfolio in that asset class. Following the introduction of this naming rule, a significant fraction of funds had to make name adjustments, as reported by Cooper et al. (2005).

Rule 35d-1 is transparent and strict concerning the asset classes, the sector, or the region in which a fund invests, whether the distribution is exempt from the income tax, and whether the fund shares are guaranteed or approved by the United States government. However, the rule is not strictly enforceable when the fund name indicates a particular focus on asset size, for example, on *small* or *large* capitalized companies. Instead, the authorities require that a fund uses "reasonable definitions of such terms", leaving room for interpretation. Some other aspects of the name are even left completely unregulated, such as a name related to a typical investment strategy (*growth* or *value*).[80]

Aware of these possible loopholes in the regulation, the SEC issued a press release in March 2020 requesting public comments about the effectiveness of Rule 35d-1. In this press release, authorities highlight the concerns linked to fund names referring to the size and investment strategy dimensions (SEC, 2020). Strongly motivated by this concern, our analysis therefore focuses on fund names referring to the size dimension (*small* or *large*) and the investment strategy dimension (*value* or *growth*).

In this paper, we do not assume that a mutual fund name is exclusive in the way that it indicates investments *only* in the suggested asset class or *only* in stocks corresponding to the specified investment style, i.e., a fund called *small* might also invest to a certain degree (much lesser) in *large* capitalized companies. Mutual fund names are only one of the information sources that investors can consult, and it should not be the only one. However, as the SEC states: "fund names are often the first piece of information investors see, and they can have a significant impact on an investment decision" (SEC, 2020). Hence, the name of a mutual fund introduces essential information to potential investors, and therefore, should not be misleading.

[80] All names are still subject to the prohibition on misleading names (SEC, 2001).

4.1.1 Literature Contribution

Regarding the existing literature, our paper builds upon the literature on inaccurate information in the mutual fund industry in general. In particular, there is a strand of literature that investigates mismatches between what mutual funds claim to do and what they actually do: mismatches between investment styles in funds' objective statements and actual investment styles (Bams, Otten, and Ramezanifar, 2017; Brown and Goetzmann, 1997; Kim, White, and Stone, 2005; Mason, Mcgroarty, and Thomas, 2012), between stated investment objectives in general and actual objectives (Kim, Shukla, and Tomas, 2000), and between the stated benchmark index and actual investment style (DiBartolomeo and Witkowski, 1997; Mateus, Mateus, and Todorovic, 2019; Sensoy, 2009) or actual holdings (Cremers and Petajisto, 2009). We contribute to this literature by providing evidence on mismatches related to the fund's name, the very first qualitative information that investors see when they invest in a mutual fund, and its actual investment style.

Second, we also contribute to the strand of literature that investigates the role of mutual fund naming in more detail. For example, Kumar, Niessen-Ruenzi, and Spalt (2015) provide evidence that U.S. investors' decisions are not free of name-induced stereotypes: funds with managers having foreign-sounding names have significantly lower annual fund flows. More closely related to our paper are two studies that report empirical evidence of misinformation related to *changes* in mutual fund names (Cooper et al., 2005; Espenlaub et al., 2017). Cooper et al. (2005) analyze fund name changes from April 1994 to July 2001 and find that funds use name changes strategically. While name-changing funds are not able to improve return-performance, they do experience significant long-term positive abnormal fund inflows. This relationship even holds for a cosmetic name change, i.e., when the portfolio holdings of the fund are not in line with its new name. Espenlaub et al. (2017) build further upon Cooper et al. (2005) and study fund name changes between 2002 and 2011, after the implementation of the SEC Names Rule in 2001. They distinguish name changes along several dimensions, among which misleadingness which corresponds to the definition of cosmetic name changes in Cooper et al. (2005).

To summarize, our contribution is fourfold. First, we analyze the problem of inaccurate fund naming by taking a broader, more continuous perspective, which is, in comparison to the above literature (Cooper et al., 2005; Espenlaub et al., 2017), not restricted to name change events. Complementary to Cooper et al. (2005) and Espenlaub et al. (2017), we provide evidence that the economic problem of inaccurate names is indeed much broader than just triggered by name change events. Instead, funds often change their investment style without changing their name, which also results in a mismatch between the fund's name and the actual strategy. Besides, we find that fund managers use name changes to solve inaccurate names. Second, we provide new insights for regulators by focusing on name dimensions, both strictly, but also less strictly regulated by the SEC Names Rule SEC (2001). Interestingly, we find fewer mismatches in the size dimension (SMB), which is stricter regulated by the SEC. In contrast, we find significant mismatches in the strategy dimension (HML), which is less strictly regulated. Third, we show that the misnaming practice can be explained by the fund industry's tournament character. Finally, we analyze the consequences of name misinformation and highlight the importance of name regulation, given investors' limited reaction to inaccurate naming.

The remainder of the paper is organized as follows. Section 4.2 describes the data collection process and provides descriptive summary statistics. In Section 4.3, we develop our accuracy classification methodology and derive the corresponding classifications for our sample. The second part of the paper elaborates on the reasons and potential consequences of inaccurate mutual fund names. Section 4.4 analyzes the funds' motivation to deviate from the investment style suggested by their name and the role played by the mutual fund tournament. In Section 4.5, we analyze the impact of fund name changes on funds' name accuracy and section 4.6 investigates the consequences of inaccurate fund names. Finally, Section 4.7 concludes.

4.2 Data

To analyze potential misleading information in mutual fund names, we construct a history of mutual fund names. To do so, we consult over 400,000 fund prospectuses available on the EDGAR database of the SEC and link the fund names to key financial data obtained from Morningstar.

4.2.1 EDGAR: Mutual Fund Names

The starting point to construct a history of mutual fund names is the open-access database EDGAR of the SEC. According to the Securities Acts of 1933 and 1940, investment companies registered with the SEC are required to disclose standardized information on their investment products, e.g., mutual funds.[81] According to the Securities Acts, funds are required to (1) update at least once a year material fund information and (2) disclose a separate filing whenever there is a significant change in this information. For completeness, we extract name information from *all* filings that investment companies of funds regularly have to provide (see Table 4.10 in the Appendix for a detailed list of filing types).

Therefore, beginning in 2010, we extract the names of a fund from each fund prospectus in the EDGAR database.[82] We analyze a total of 418,938 prospectuses that were filed between January 2010 and December 2018. We then aggregate the information from these different filings and construct a monthly fund name history database of 20,973 funds (see Table 4.10 in the Appendix for the details).

4.2.2 Morningstar: Financial Data of Mutual Funds

The names history database is merged with the survivorship bias-free mutual fund database of Morningstar that includes information on fund returns, various risk measures, as well as several mutual fund characteristics, such as total assets under management, costs, and security holdings.[83]

In order to analyze investors' reactions, we compute the fund quarterly net flows. Based on data on total net assets and returns, we then compute quarterly fund net flows, which we define as the growth rate of the total assets under management adjusted for reinvested returns:

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t})}{TNA_{i,t-1}(1 + R_{i,t})}, \tag{4.1}$$

where $TNA_{i,t}$ is fund i's total net assets in quarter t and $R_{i,t}$ is the fund's return over the

[81] There is a relatively young research stream on information from mutual fund prospectuses (see Abis, 2017; Baghai et al., 2019; Hillert et al., 2016; Kostovetsky and Warner, 2020; Krakow and Schäfer, 2020). Abis (2017) applies machine learning techniques to the strategy section of mutual fund prospectuses to classify funds as either quantitative or discretionary. Baghai et al. (2019) retrieve information on the use of credit ratings from mutual fund prospectuses. Hillert et al. (2016) analyze the tone in mutual fund letters, which they also extract from the same database. Krakow and Schäfer (2020) provide evidence that qualitative updates in fund prospectuses are informative.

[82] We choose 2010 since from that year onward, prospectus data is provided in the eXtensible Business Reporting Language (XBRL) format. Therefore, the extraction of relevant sections in a prospectus can be identified due to the XBRLkey structure.

[83] As many funds are offered in multiple share classes, which all belong to the same fund and therefore also have the same fund name, we aggregate the Morningstar share class-level information into fund-level information. This aggregation is done by taking the market value-weighted average (see, e.g., Kacperczyk et al. (2008); Gallaher et al. (2015); Choi et al. (2016)). The oldest share class is used as the reference for all the other variables for which no aggregation is needed.

prior quarter.[84] To account for outliers, we winsorize at the 1% level at the bottom and the top parts of the distribution.

While data is mostly available on a monthly basis, we aggregate it to a quarterly frequency. We do this to avoid too much variability in factor loadings when using short samples. Name changes within a quarter are handled in the following way. If a fund changes its name in the first half of the quarter, we assign the new name to the corresponding quarter. If the fund changes its name in the second half, we assign the new name only to the next quarter. Finally, we restrict the sample to equity funds only and exclude funds with less than 1 million assets under management and funds with only one quarter of observations.

4.2.3 Descriptive Statistics

Our final sample consists of 2,126 U.S. equity open-end mutual funds that are linked to 2,669 different names in the period 2010 to 2018. Of those funds, 1,339 funds have a name which either refers to the SMB dimension (having the terms *small* or *large* in the name) or to the HML dimension (having the terms *growth* or *value* in the name), or jointly to both dimensions. Table 4.1 reveals that the number of funds that refer to a specific style is relatively constant over time. A large fraction of funds refers to the HML dimension only, while most funds that refer to the SMB dimension also refer to the HML dimension.

Table 4.2 reports sample summary statistics on various portfolio characteristics. The average fund has assets under management of USD 2,709 million, is 16 years old, and charges a quarterly gross expense ratio of 0.12%. The average quarterly fund flow is 2.19%, the average investor's return (net of costs) over a quarter is 1.18%, and the idiosyncratic risk of a fund in a quarter is 0.34%.

4.3 Inaccurate Mutual Fund Names

To answer our research questions, we first analyze the prevalence of inaccurate naming practices by studying the alignment between mutual fund names and investment styles.

[84]This measure follows the methodology of Huang et al. (2011). Most studies define fund's net flows as $Flow_{i,t} = (TNA_{i,t} - TNA_{i,t-1}(1+R_{i,t}))/(TNA_{i,t-1})$. However, our approach, following the methodology of Huang et al. (2011), guarantees that fund outflows will not be below -100%. The Pearson correlation coefficient between the two measures is 0.998.

Table 4.1: **Description of mutual fund names**

Table 4.1 shows the number of fund names in each year that indicate a fund's investment style. Funds are defined as having a style name if one of the following style identifiers appears in their name: "large/lg/blue chip", "small/sml/sm", "growth/grth/gr", and "value/val". The sample consists of all U.S. open-end equity mutual fund names which are retrieved from the SEC database and linked to the Morningstar data over the 2010 to 2018 period.

Dimension	2010	2011	2012	2013	2014	2015	2016	2017	2018
Small	122	131	111	114	116	129	131	144	147
Small & Growth	70	75	60	59	61	63	63	67	70
Small & Value	84	93	76	78	80	85	88	86	86
Large	62	58	46	38	38	42	48	53	60
Large & Growth	79	83	63	56	55	49	48	50	52
Large & Value	77	78	63	57	52	51	54	55	56
Growth	273	281	212	209	204	206	202	217	212
Value	203	215	174	160	151	155	155	167	165
Other	591	612	519	492	472	473	495	553	560
Total	1561	1626	1324	1263	1229	1253	1284	1392	1408

To do so, we rely on a return-based analysis (see, e.g., Cooper et al., 2005).[85] The motivation for such a return-based method is threefold. First, funds' returns provide timely information about the funds' investment style as it is available at a daily frequency, while portfolio holdings data is only updated quarterly. Second, and related, this information is much more sensitive to changes in investment style than the information about portfolio holdings (see, e.g., ter Horst, Nijman, and de Roon, 2004). Third, while mutual funds report on a quarterly basis their holdings themselves, returns are publicly observable and are therefore exempt from possible reporting biases.

For each fund, for each quarter, we estimate the four-factor model of Carhart (1997) on daily returns. The factors are obtained from Kenneth French's website.[86] Specifically,

[85] Cooper et al. (2005) use such a method to identify inaccurate name changes, i.e., a fund name which refers after a name change to an investment style that does not correspond to the portfolio holdings.

[86] We thank Kenneth French for providing data on these factors. For more details, see `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

Table 4.2: **Characteristics of the funds in the sample**

Table 4.2 shows summary statistics (mean, standard deviation, median, first (p1) and last (p99) percentile. All fund characteristics are defined in detail in Table 4.14. The variables *Fund Flow* and *Expense Ratio* are winsorized at the bottom and the top percentile. The variable *Age* is calculated based on the IPO of the oldest share class. The variable *Idiosyncratic Risk* is the standard deviation of the residual of the Carhart (1997) four-factor model.

Variable	Mean	Std	p1	Median	p99
Fund Flow (in %)	2.19	14.06	-29.61	0.52	81.17
Fund Size (in mn. $)	2709.93	14,568.09	1.53	372.75	43,069.68
log(Fund Size (in mn. $))	19.60	2.18	14.24	19.74	24.49
log(Company Size)	21.80	2.11	16.06	22.07	25.87
Age (in Years)	16.21	12.64	0.83	14.25	74.38
log(Age (in Years))	2.49	0.86	-0.18	2.66	4.31
Return (in %)	1.18	5.06	-18.26	1.15	13.28
Idiosyncratic Risk (in %)	0.34	0.48	0.04	0.21	2.35
Expense Ratio (in %)	0.12	0.09	0.01	0.09	0.50
Turnover Ratio (in %)	68.77	95.33	2.00	46.61	500.35
Cash Proportion (in %)	2.86	8.64	-0.98	1.86	28.18
FI Proportion (in %)	0.55	7.93	0.00	0.00	7.84
Equity Proportion (in %)	95.95	8.84	58.02	97.71	100.26
Holdings	216.80	404.57	17.33	90.00	2274.00

we estimate the following model for each quarter:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{R,i}(R_{M,t} - R_{f,t}) + \beta_{S,i}SMB_t + \beta_{H,i}HML_t + \beta_{M,i}MOM_t + \epsilon_{i,t}, \quad (4.2)$$

where $R_{i,t}$ is the return of fund i on day t, and $R_{f,t}$ the risk-free rate. $R_{M,t}$, SMB_t, HML_t and MOM_t denote the market, size, value-growth, and momentum returns on day t, respectively.

Thus, as a result, we obtain quarterly factor loadings for each fund. Next, to determine inaccurate fund names, we focus on two of these loadings: $\beta_{S,i}$ and $\beta_{H,i}$. In particular, we use $\beta_{S,i}$ to identify a name referring to the size (SMB) dimension, i.e. using the terms *small* or *large*. Similarly, we use $\beta_{H,i}$ to identify names referring to the investment strategy

(HML) dimension, i.e. including the terms *growth* or *value*.

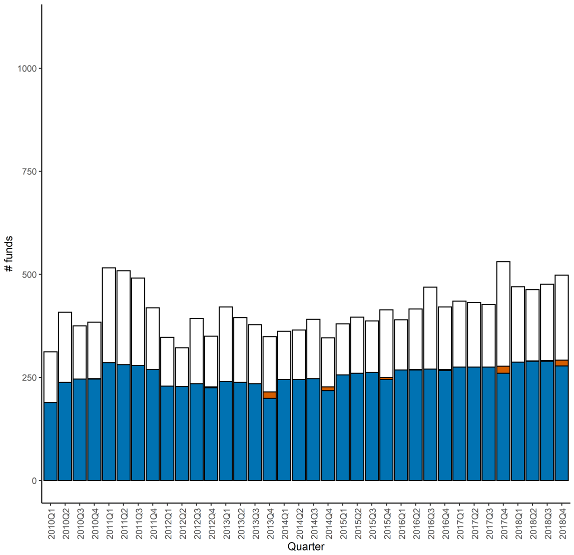
For each of these two factor loadings, we use cluster analysis to sort funds into two investment style clusters according to their similarity in $\beta_{S,i}$ or $\beta_{H,i}$. The goal of this cluster analysis is to obtain a high similarity in $\beta_{\cdot,i}$ between funds in the same group and low similarity between funds in different groups (see, e.g., Jain, 2010). Based on the classification of a fund in a group, we can then determine whether the name information is in line with the investment style cluster, and thus whether the name is accurate or not.

A few other papers also use cluster analysis in the context of mutual funds. For example, Brown and Goetzmann (1997) and Mason et al. (2012) use the most popular algorithm, K-means (Jain, 2010), to classify funds into different style groups. The goal of the K-means algorithm is to allocate funds to a pre-specified number of groups by minimizing the squared error between the group's empirical mean and the funds in this group (Jain, 2010). Despite being intuitive and widely used, this clustering technique has one undesirable property: it is a *hard* assignment, meaning that each fund is assigned to a single cluster. An extension of the K-means algorithm, called fuzzy C-means (Dunn, 1973; Bezdek, 1981), overcomes this by allowing each fund to be part of every group, but with different degrees of membership. For example, in the case of two groups, the fuzzy C-means algorithm identifies the degree of membership of a fund to the first group (say, 0.2) and the second group (say, 0.8). Since the degrees of membership sum up to one, we can interpret them as the likelihood that a fund belongs to each of the groups.

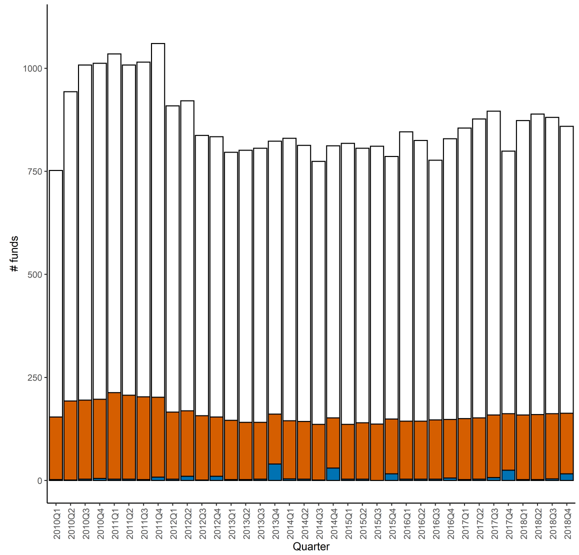
In this paper, we use the fuzzy C-means algorithm and interpret the degree of membership of a fund to the wrong cluster as the *degree of inaccuracy* of its name. For example, if a fund name includes the word *small* but belongs to the group *large* with a degree of membership of 0.7, we conclude that this fund name has a degree of inaccuracy of 0.7. Similarly, if a fund name includes the word *value* and belongs to the group *growth* with a degree of membership of 0.1, we conclude that this fund name has a degree of inaccuracy of 0.1.

To determine the name of each group, we look at the names of funds that belong to each group with a degree of membership of at least 0.5, as these funds are more likely to belong to this group than to the other one. Suppose the majority of funds in a group has a name including the word *small* (vs. *large*), this group is labeled *small*.[87]

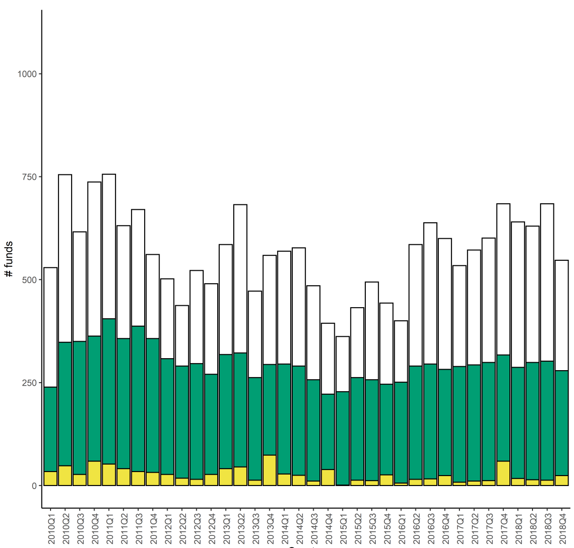
[87]When using a clustering algorithm as fuzzy C-means or K-means, one should know that the different initial partitions might lead to different cluster results. However, this is not a concern for us: as suggested in Jain (2010), we run for robustness the clustering algorithm with several initial partitions, and the *inaccurate* dummy variable remains the same.



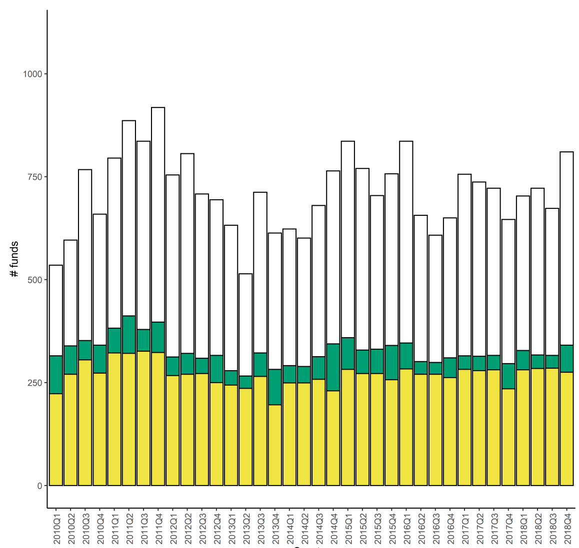
(a) **Panel A: Cluster *Small***



(b) **Panel B: Cluster *Large***



(c) **Panel C: Cluster *Growth***



(d) **Panel D: Cluster *Value***

Figure 4.1: **Number of funds per cluster per year quarter**

Figure 4.1 shows the number of funds per cluster per year quarter. In Panels A and B, funds whose name contain the word *small* are in blue and funds with the word *large* in their name are in red. Other fund names are in white. In Panels C and D, fund names referring to *growth* are in green and funds having the word *value* in their name are in yellow. Other names are in white. In total, the sample consists of 2,743 fund names between 2010 and 2018.

Finally, based on this degree of inaccuracy, we also create a dummy variable *inaccurate*. When a fund's degree of membership to the wrong group is higher than or equal to 0.5, we identify this fund's name as inaccurate. In the example above, the fund featuring the term *small* in its name is inaccurate, while the fund featuring the word *value* in its name is accurate.

Figure 4.1 illustrates the results of the cluster analysis. First, the classification of each cluster is straightforward as each cluster is dominated by funds having a specific term in their name (either *small* or *large* for the cluster on the SMB dimension determined using $\beta_{S,i}$, and either *growth* or *value* for the cluster on the HML dimension determined using $\beta_{H,i}$). Second, there is some heterogeneity across the dimensions and also across time. For instance, a larger fraction of HML funds is classified as inaccurate compared to SMB funds.

More detailed information on the proportion of inaccurate fund names, per year, per type of fund name, and per dimension on which they are inaccurate is reported in Table 4.3.[88] On average, each year, around 25% of funds in our sample is inaccurate in at least one dimension. This proportion slightly varies over time but always remains above 18%. The phenomenon of inaccurate naming, therefore, tends to be widespread. Looking at the specific dimensions of inaccuracy, we see that a much bigger proportion of funds is inaccurate on the HML dimension than on the SMB dimension. This finding is not surprising given that, according to the SEC Names Rule (35d-1), names referring to the SMB dimension must be used in a "reasonable manner", while there is no such clear restriction for names referring to the HML dimension (SEC, 2001). The findings, therefore, suggest that a Names Rule is effective. Finally, we find that only a very small proportion of funds is inaccurate on both dimensions.

Focusing on the results per type of name, Table 4.3 reveals that the funds that most often feature an inaccurate name are those referring to the two terms *small & growth* in their name. More than 30% of these fund names are indeed found to be inaccurate every year. On the other end of the spectrum, the funds featuring the term *large* are very rarely classified as being inaccurate.

[88]When a fund name contains both a term referring to the SMB dimension (*small* or *large*) and a term referring to the HML dimension (*value* or *growth*), it can be found to be inaccurate either on the SMB dimension, or on the HML dimension, or on both dimensions. Hence, there are in total 8 possible accurate/inaccurate name cases. Table 4.11 displays the various cases.

Table 4.3: **Inaccurate mutual fund names**

Table 4.3 shows the proportion (in %) of fund names which are found to be inaccurate each year, per type of name, and per dimension on which they are found to be inaccurate. SMB refers to inaccurate fund names associated with the SMB dimension (cases (2) and (6) in Table 4.11). HML refers to inaccurate fund names associated with the HML dimension (cases (4) and (7)). SMB & HML refers to inaccurate fund names associated with both dimensions (case (8)). Note that the number in All is not necessarily the sum of the numbers in SMB, HML, and SMB & HML. Indeed, a fund name related to two dimensions (*small & value* for example), can be inaccurate on the different dimensions during the year. For example, in a given quarter of a year, the use of *small* is inaccurate while the use of *value* is accurate, and on another quarter of the same year the use of both *small* and *value* is inaccurate. So, this fund name is included in once on row All, as well as once on row SMB and once on row SMB & HML.

Name	2010	2011	2012	2013	2014	2015	2016	2017	2018
All funds									
All	28.56	22.09	20.75	36.06	31.70	25.51	18.12	23.24	20.75
SMB	0.93	0.89	2.61	5.71	3.96	2.56	1.65	5.36	3.89
HML	27.73	21.40	18.51	29.18	26.68	22.31	16.35	17.52	16.75
SMB & HML	0.00	0.20	0.12	2.08	1.45	0.90	0.13	0.72	0.47
Small	3.28	3.82	9.91	15.79	12.07	5.43	3.82	12.50	9.52
Small & Growth	75.71	56.00	65.00	69.49	60.66	57.14	36.51	31.34	35.71
SMB	0.00	2.67	11.67	16.95	9.84	4.76	3.17	4.48	4.29
HML	75.71	56.00	58.33	59.32	52.46	50.79	33.33	25.37	34.29
SMB & HML	0.00	1.33	1.67	3.39	1.64	3.17	0.00	2.99	1.43
Small & Value	10.71	4.30	7.89	37.18	23.75	16.47	9.09	19.77	9.30
SMB	4.76	2.15	1.32	10.26	10.00	8.24	3.41	10.47	1.16
HML	5.95	2.15	6.58	20.51	11.25	4.71	4.55	9.30	6.98
SMB & HML	0.00	1.08	0.00	7.69	3.75	3.53	1.14	2.33	1.16
Large	0.00	0.00	0.00	7.89	0.00	2.38	0.00	9.43	10.00
Large & Growth	3.80	6.02	7.94	26.79	25.45	24.49	12.50	16.00	17.31
SMB	1.27	0.00	3.17	3.57	0.00	4.08	4.17	10.00	7.69
HML	3.80	6.02	4.76	8.93	14.55	20.41	8.33	6.00	5.77
SMB & HML	0.00	0.00	0.00	14.29	10.91	4.08	0.00	0.00	3.85

Table 4.3 continued.

Large & Value	22.08	14.10	11.11	36.84	26.92	17.65	16.67	23.64	19.64
SMB	0.00	0.00	0.00	5.26	3.85	0.00	1.85	9.09	8.93
HML	22.08	14.10	11.11	31.58	21.15	17.65	14.81	10.91	12.50
SMB & HML	0.00	0.00	0.00	0.00	1.92	0.00	0.00	3.64	0.00
Growth	41.76	31.67	27.83	36.84	46.08	46.60	33.17	29.03	32.08
Value	37.93	31.63	22.99	46.25	31.79	15.48	16.13	29.94	21.21

In addition, we also provide descriptive statistics about the prevalence of this practice of inaccurate naming per fund, i.e., is a fund inaccurate just once or twice in its life-cycle or does it occur more frequently. Figure 4.2 sheds light on this issue and shows that a large fraction of funds indeed provides inaccurate information for just a limited number of times, but an important fraction of funds do exhibit such misnaming practice for many periods; with some funds even having an inaccurate name for as long as 8 years (almost the entire sample period). Such high frequencies hint at a rather deliberative process by the fund managers involved.

Finally, we also provide descriptive evidence on the distribution of the inaccuracies over the quarters in a year. In line with the tournament hypothesis that is analyzed in the next section, Table 4.4 indeed confirms that most inaccuracies occur during the fourth quarter of a given year. This non-random pattern suggests that the practice is intentional.

4.4 Reasons for Inaccurate Fund Names: the Tournament Hypothesis

In this section, we focus on the reasons for the observed deviations in the name dimension as motivated by the tournament hypothesis of Brown et al. (1996) and Chevalier and Ellison (1997). More precisely, five elements are combined to develop this hypothesis. First, the mutual fund industry can be seen as a tournament in which funds with similar investment styles compete with each other.[89] The funds at the top of the ranking within a style group win the tournament, while those at the bottom lose it. Second, the vast

[89]This tournament characteristic is, for instance, illustrated by the periodic performance ranking of funds by business magazines and financial service firms.

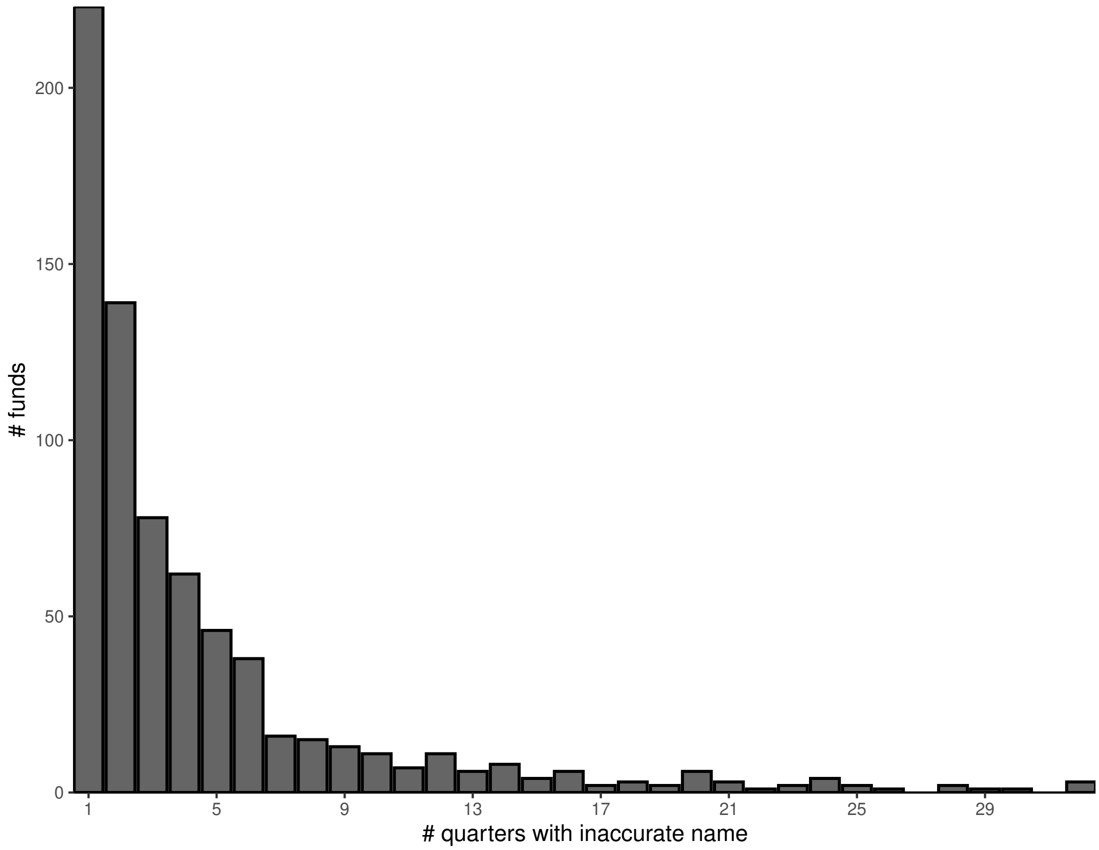


Figure 4.2: **Frequency of inaccurate fund names**

Figure 4.2 shows the number of funds having an inaccurate name for a given number of quarters. In total, the sample consists of 3,008 inaccurate fund-quarter observations between 2010 and 2018.

majority of these rankings are produced at the end of a calendar year, based on funds' performance over the year (Brown et al., 1996). Third, according to the tournament hypothesis, the funds appearing at the top of these end-of-year rankings, i.e., the winners of the tournament, receive higher fund inflows as compared to the losers (Brown et al., 1996). Fourth, in contrast to the fund inflows for the winners, there are no significant fund outflows for the loser. Hence, there is empirical evidence for an asymmetric return-flow relationship (Brown et al., 1996; Chevalier and Ellison, 1997). While funds with better performance are rewarded with higher inflows of money, worse-performing funds do not necessarily suffer from outflows. Fifth, managers' compensation is determined based on (new) assets under management. Therefore, their compensation is positively related to the amount of money flowing into the fund (Brown et al., 1996), giving them strong incentives to be among the winners at the end of the year.

Assembling these puzzle pieces results in the following hypothesis. As managers' compensation is linked to fund's inflows, which, in turn, is the consequence of better performance, managers have incentives to be among the end-of-year winners. For this reason, when their performance over the course of a year is worse than their competitors', they have an incentive to deviate from the investment style stated in their name in an attempt to catch up with competitors by the end of the year, when rankings are finalized. If this deviation is successful, their funds will receive higher new investments, and their compensation will increase. This behavior can be explained with prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). Due to the convexity of the utility function in the loss area, individuals are willing to take more risk. However, given the asymmetric return-flow relationship, if this deviation is not successful and leads to worse end-of-year performance, managers would, on the other hand, not necessarily be penalized by investment outflows, and their compensation would not be drastically affected.

In the context of the name inaccuracy, the tournament hypothesis can be supported by three different pieces of evidence. First, if the tournament hypothesis holds, funds would deviate more often at the end of the year Hence, we expect fund name deviations to happen mainly during the fourth quarter of a year. This hypothesis is motivated by the attempt to catch up with the winning funds by the end of the year when performance rankings are calculated. Second, the rank of a fund's performance in comparison to its competitors would determine the degree to which a fund deviates from the stated investment style, i.e., the degree of inaccuracy: the lower the rank, the higher the incentive to "gamble" and to deviate from the stated investment style. Third, as the tournament hypothesis implies that the decision to deviate is deliberate and is part of a strategy, we expect a difference between funds whose names are only inaccurate for one quarter (which could be due to inattention) and funds whose names are inaccurate for multiple quarters. A repetitive character would indeed point at a deliberate strategy used by managers rather than inattention. In particular, the performance ranking would determine the degree of inaccuracy of funds whose names are inaccurate for at least two quarters. This would not be the case for funds featuring an inaccurate name for only one quarter.

Hence, in what follows, we provide evidence for the support of the tournament hypothesis. First, we look at the timing of the inaccuracy to identify potential patterns. Second, we analyze the determinants of the degree of inaccuracy and investigate whether performance ranking is indeed a significant determinant of a fund's inaccuracy. Finally, we distinguish funds deviating for only one quarter from funds deviating for at least two quarters and conduct the previous analysis on each sample separately.

4.4.1 Point in Time of the Inaccuracy

First, we look at the distribution of inaccurate mutual fund names over the year. Table 4.4 reports the percentage of funds deviating in each quarter.[90] The results show that most deviations (53%) occur during the last quarter of a year, while the rest is equally distributed among the other three quarters. Accordingly, most fund name deviations come up at the end of the year, when relative performance rankings are created. Thus, this finding is in line with the tournament hypothesis, which predicts that funds would deviate from their stated investment strategy in an attempt to increase their performance and catch up with best-ranked competitors by the end of the year when performance rankings are issued. Interestingly, this result holds for all dimensions but amplifies in the more strictly regulated dimensions (SMB or SMB & HML), in which we observe, in general, fewer deviations (see Table 4.3).

Table 4.4: **Quarter of deviation**

Table 4.4 reports the deviations (in %) from the investment style suggested by the name (fund names switching from being accurate to being inaccurate) per quarter and per dimension (SMB, HML, or both SMB & HML).

	Q1	Q2	Q3	Q4
All	14	17	15	53
SMB	6	12	7	75
HML	16	19	17	48
SMB & HML	0	0	0	100

4.4.2 Determinants of Inaccuracy and Fund's Performance Rank

Next, we investigate which determinants explain the degree of inaccuracy of mutual fund names, i.e., the degree to which a fund deviates from the investment styles stated

[90] To make results across categories comparable, we report relative and not absolute numbers.

in its fund name. In particular, we are interested in whether the performance rank determines the degree to which funds deviate.

To this end, we estimate a panel regression in which the dependent variable is the degree of inaccuracy. We relate this inaccuracy to various fund characteristics observed in the previous quarter. Among others, we test for the impact of past fund flows, fund age, costs, and risk. Following Cooper et al. (2005) and Espenlaub et al. (2017), we also include a long-term flow variable, computed as the average of the fund flows over the previous three quarters. Including this variable allows us to identify whether the relationship between flows and inaccuracy is rather of long- or short-term nature. Further, we include the rank of a fund based on its return with respect to its competitors, defined as the funds having the same name; i.e. a fund named *small* competes with all the other funds named *small*. We compute the fund's rank on the basis of their returns earned over the past three quarters. Finally, we control for general market conditions by including quarter fixed effects. The samples of funds in this analysis are the one defined in Table 4.12.[91] Hence, we estimate the following panel regression model:

$$\begin{aligned}\text{Inaccuracy}_{f,t} =& \gamma_0 + \gamma_1 \text{Rank}_{f,[t-3,t-1]} + \gamma_2 \text{Fund Flow}_{f,t-1} + \gamma_3 \text{Mean Flow}_{f,[t-3,t-1]} \\ &+ \gamma_4 \text{Risk}_{f,t-1}) + \gamma_5 \text{Fund Size}_{f,t-1} + \gamma_6 \log(\text{Age}_{f,t-1}) \\ &+ \gamma_7 \text{Expense Ratio}_{f,t-1} + \gamma_8 \text{Turnover Ratio}_{f,t-1} + \nu_t + \epsilon_{f,t-1}, \qquad (4.3)\end{aligned}$$

where $\text{Inaccuracy}_{f,t-1}$ is the degree of inaccuracy at time t of fund f. $\text{Rank}_{f,[t-3,t-1]}$ is the respective rank variable. Further, we control for the fund flow and the return, the fund risk, size, the age, the expense ratio, and the turnover. ν_t is a year-quarter fixed effect, and we cluster standard errors at the fund level. The coefficient of interest with respect to the tournament hypothesis, γ_1, captures the marginal effect of the fund's respective rank on the degree of inaccuracy and indicates whether its relative performance drives the degree of a fund's inaccuracy. The results for our sample of funds that have a name referring to either the size (SMB), the investment strategy (HML) dimension, or both dimensions at the same time are reported in Table 4.5.

Indeed, results in Table 4.5 support our hypothesis: the lower the rank of a fund's performance with respect to its competitors, the higher the degree to which the fund deviates from the investment style stated in its name. Thus, this finding suggests that funds that are relative losers change investment styles that are not aligned with their

[91]Note that we lose some observations given that the explanatory variables are lagged by one quarter, or are sometimes computed using information over three quarters.

Table 4.5: **Determinants of Inaccuracy**

Table 4.5 reports the result of a panel regression investigating the determinants of the degree of inaccuracy of a fund (i.e. the degree to which a fund deviates from the investment style stated in its name). The samples are as defined in Table 4.12. Quarter fixed effects are used. The dependent variable *Inaccuracy* is between 0 and 100. The independent variables are all standardized. The determinants are defined in Table 4.14. Column (1) reports the results for the whole sample of funds, column (2) reports the results for funds with a name related to the SMB dimension, column (3) reports the results for funds with a name related to the HML dimension, and column (4) reports the results for funds with a name related to both the SMB and HML dimensions. The standard errors are clustered at the fund level and are reported in parentheses. * , **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) All	(2) SMB	(3) HML	(4) SMB & HML
$\text{Rank}_{[t-3,t-1]}$	-0.6604***	-0.4721***	-0.8466***	-0.3451**
	(0.1871)	(0.1646)	(0.2171)	(0.1687)
Fund Flow_{t-1}	0.2199	0.0500	0.3550*	0.0904
	(0.1704)	(0.1511)	(0.2043)	(0.1559)
Mean $\text{Flow}_{[t-3,t-1]}$	-1.0262***	-0.6360***	-0.6959***	-0.2114
	(0.2035)	(0.1743)	(0.2443)	(0.1998)
Risk_{t-1}	0.5625***	0.6204***	0.4041*	0.4365**
	(0.1889)	(0.1644)	(0.2101)	(0.1812)
Fund Size_{t-1}	-0.0347	-0.0717	-0.0519	-0.1196
	(0.3619)	(0.3181)	(0.3990)	(0.3151)
$\log(\text{Age})_{t-1}$	0.3218	0.1670	0.2442	0.0468
	(0.2823)	(0.2233)	(0.3090)	(0.2229)
Expense ratio_{t-1}	1.8346***	0.4741	2.6273***	0.7229**
	(0.3639)	(0.3098)	(0.3715)	(0.2998)
Turnover_{t-1}	0.1304	0.1924	-0.1019	0.0714
	(0.2958)	(0.2049)	(0.3436)	(0.2751)
Quarter Fixed Effect	Y	Y	Y	Y
Observations	19,662	10,466	15,055	5,937
Adj. R^2	0.0753	0.062	0.0693	0.0564

names to improve their relative performance. This relation holds no matter the dimension on which the fund name is inaccurate (SMB, HML, or both). In column (2), (3), and (4) of Table 4.5, we separate the analysis between funds that provide a size indication in their name (column (2)), those that indicate an investment strategy (column (3)), and those that refer to both dimensions (column (4)). The main results are always similar to the regression that includes all funds.

In addition to the performance ranking, other variables are found to be significant determinants. One of them is fund risk. When a fund has higher idiosyncratic risk, it deviates more from the stated investment style. This is also true, no matter the dimension in which a name can be inaccurate.

Moreover, we find a significant effect of fund flows on the degree of inaccuracy. The fund flows in the previous three quarters are significantly negatively related to the degree to which a fund deviates from its suggested investment strategy in the name. Interestingly, we do not find that the most recent fund flows from the previous quarter are significantly determining the degree of inaccuracy, which suggests that the identified relation is more of a long-term than a short-term nature.

Finally, we find a statistically significant relationship between a fund's expense ratio and the degree of a fund's name inaccuracy. The more expensive a fund is, the higher is the degree to which it deviates. We also include fund size, age, and turnover in the preceding quarter to analyze whether larger, older and more active funds have a higher probability of providing an inaccurate fund name but do not find any significant impact.

4.4.3 Inattention vs. Deliberate Strategy

While the results in Table 4.5 support our hypothesis and provide evidence that managers' decisions to deviate from the strategy are linked to a relatively bad rank in performance in the previous quarters, we cannot rule out that a deviation can also happen by inattention. Hence, in the next step, we test whether this decision is based on a manager's inattention or whether it is because of a deliberate strategy.

For this reason, and to refine our analysis, we perform the same regression but splitting our sample into two different subsamples. Figure 4.2 in Section 4.3 shows that a large fraction of funds provides only for a very short time an inaccurate fund name, while other funds do so for a long time. Hence, we test whether funds that differ in the duration of inaccurate information also differ with respect to the motivation. The implicit assumption behind this analysis is that short-term inaccuracy represents an inattention motive rather while a deliberate strategy would drive long-term inaccuracy.

Table 4.6: **Determinants of inaccuracy: restricted sample (0/1)**

Table 4.6 reports the result of a panel regression to investigate the determinants of the degree of inaccuracy of a fund (i.e. the degree to which a fund deviates from the investment style stated in its name). Starting from the sample as defined in Table 4.12, we restrict this analysis to the subsample of funds whose names are never inaccurate or are inaccurate for a single quarter only. The determinants are defined in Table 4.14. Quarter fixed effects are used. The variables are all standardized. Column (1) reports the results for the whole sample of funds, column (2) reports the results for funds with a name related to the SMB dimension, column (3) reports the results for funds with a name related to the HML dimension, and column (4) reports the results for funds with a name related to both the SMB and HML dimensions. The standard errors are clustered at the fund level and are reported in parentheses. * , **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) All	(2) SMB	(3) HML	(4) SMB & HML
$\text{Rank}_{[t-3,t-1]}$	-0.1620	-0.1940	-0.2656	-0.1373
	(0.1368)	(0.1514)	(0.1700)	(0.1978)
Fund Flow_{t-1}	0.1294	0.1230	0.1649	0.2774*
	(0.1263)	(0.1153)	(0.1643)	(0.1448)
$\text{Mean Flow}_{[t-3,t-1]}$	-0.6095***	-0.5482***	-0.3806**	-0.1731
	(0.1413)	(0.1586)	(0.1708)	(0.1977)
Risk_{t-1}	0.3448***	0.2389**	0.3337**	0.1622
	(0.1271)	(0.1144)	(0.1578)	(0.1478)
Fund Size_{t-1}	0.1217	-0.1122	0.1711	-0.3400
	(0.2419)	(0.2910)	(0.2677)	(0.3295)
$\log(\text{Age})_{t-1}$	-0.1043	-0.0533	-0.1626	-0.0601
	(0.1880)	(0.2241)	(0.2091)	(0.2644)
$\text{Expense ratio}_{t-1}$	0.2562	-0.0523	0.7668***	-0.0497
	(0.2305)	(0.2611)	(0.2384)	(0.3023)
Turnover_{t-1}	0.3787**	0.4568**	0.1815	0.0454
	(0.1489)	(0.1980)	(0.2028)	(0.3721)
Quarter Fixed Effect	Y	Y	Y	Y
Observations	11,453	7271	7511	3343
Adj. R^2	0.0488	0.0533	0.0373	0.0303

Table 4.7: **Determinants of inaccuracy: restricted sample (0/>1).**

Table 4.7 reports the result of a panel regression to investigate the determinants of funds the degree of inaccuracy of a fund (i.e. the degree to which a fund deviates from the investment style stated in its name). Starting from the sample as defined in Table 4.12, we restrict this analysis to the subsample of funds whose names are never inaccurate or are inaccurate for more than a single quarter. The determinants are defined in Table 4.14. Quarter fixed effects are used. The variables are all standardized. Column (1) reports the results for the whole sample of funds, column (2) reports the results for funds with a name related to the SMB dimension, column (3) reports the results for funds with a name related to the HML dimension, and column (4) reports the results for funds with a name related to both the SMB and HML dimensions. The standard errors are clustered at the fund level and are reported in parentheses. * , **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) All	(2) SMB	(3) HML	(4) SMB & HML
$\text{Rank}_{[t-3,t-1]}$	-0.7607***	-0.4131**	-1.0088***	-0.3969**
	(0.2200)	(0.1921)	(0.2534)	(0.1913)
Fund Flow_{t-1}	0.1564	-0.0005	0.3298	0.0334
	(0.1886)	(0.1664)	(0.2292)	(0.1849)
$\text{Mean Flow}_{[t-3,t-1]}$	-0.9502***	-0.5320***	-0.5688**	-0.1403
	(0.2390)	(0.1986)	(0.2857)	(0.2357)
Risk_{t-1}	0.8146***	0.8506***	0.4897**	0.4323**
	(0.2369)	(0.2261)	(0.2463)	(0.2085)
Fund Size_{t-1}	-0.2229	-0.2128	-0.2659	-0.1047
	(0.4392)	(0.3801)	(0.4791)	(0.3620)
$\log(\text{Age})_{t-1}$	0.5863*	0.3052	0.4695	0.0256
	(0.3348)	(0.2662)	(0.3619)	(0.2513)
$\text{Expense Ratio}_{t-1}$	2.0122***	0.4876	2.7936***	0.9189***
	(0.4241)	(0.3648)	(0.4319)	(0.3349)
Turnover_{t-1}	0.1781	0.2565	-0.1283	0.1982
	(0.3530)	(0.2201)	(0.4033)	(0.2685)
Quarter Fixed Effect	Y	Y	Y	Y
Observations	15,637	8181	12,033	4641
Adj. R^2	0.0712	0.0475	0.0698	0.0562

First, we analyze funds whose names are only inaccurate for a single quarter (inattention treatment) versus funds whose names are never inaccurate (control group). Second, we study funds whose names are inaccurate for more than one quarter (deliberate strategy treatment) versus funds whose names are never inaccurate (control group). We use the repetitive nature of a name inaccuracy as an indication that the decision to deviate is part of the fund's strategy to achieve a higher rank. The tournament hypothesis implies that the rank is significant only for the regression, where the treatment group consists of funds whose names are inaccurate for more than one quarter.

Table 4.6 reports the result of the regression estimated on a sample of funds that either never have an inaccurate name or have an inaccurate name for only one quarter, while Table 4.7 estimates the regression on a sample including the funds that have an inaccurate name for more than one quarter.

The results of Table 4.6 and 4.7 support the tournament hypothesis as Table 4.6 does not report any effect of the rank on the degree of inaccuracy while Table 4.7 reports such an impact. The performance rank over the past quarters does not drive the degree of inaccuracy of funds that are only short-term inaccurate in their names. In contrast, we find for long-term inaccurate mutual fund names that the lower the rank of a fund's performance with respect to its competitors, the higher the fund's degree deviates from the investment style stated in its name. The results hold across all dimensions.

Therefore, we conclude that the results of our analyses confirm that managers use deviations from the investment styles stated in the name (leading to an inaccurate name) as a strategy when their performance over the course of the year is worse than their competitors, to try to achieve a higher performance rank by the end of the year when rankings are issued.

4.5 Fund Name Changes and Inaccuracy

In general, fund managers are allowed to change the fund names whenever they want as long as the new name is in line with Rule 35d-1 (SEC, 2001). In doing so, fund managers can ensure that the new fund name is continuously accurate with regard to the asset class, the sector, or the region in which a fund invests. Former literature documents that fund name changes are widespread and used as a strategic instrument (Cooper et al., 2005; Espenlaub et al., 2017). Namely, fund managers use name changes to attract fund inflows, i.e., changing the name from a cold fund name (style) to a hot fund name (style).

This, however, sometimes also without considering the accuracy of the new fund name.

Hence, fund name changes can affect the degree of inaccuracy of a name in two possible ways. On the one hand, they can increase the inaccuracy of a name. This is the case when a fund manager changes the fund name without changing the underlying portfolio. This is what Cooper et al. (2005) and Espenlaub et al. (2017) observe: a new fund name can indicate an investment in hot styles without being accompanied by a corresponding change in the portfolio. On the other hand, name changes can decrease the inaccuracy of a fund name. This happens when a fund name and the corresponding fund portfolio are not aligned before the fund name change. In this case, a fund manager changes the fund name to ensure that the name remains in line with a new portfolio.

Accordingly, we investigate in the following the role of fund name changes for the accuracy of the name and thus analyze all fund name changes in our sample between 2010 and 2018. In total, there are 665 fund name changes. See Figure 4.3 for an overview of fund name changes over time.

Figure 4.3 shows the number of fund name changes in each year quarter. It illustrates that fund name changes are spread over the whole period in our sample. On average, there are 18 fund name changes per quarter with a considerable variation over time.

Next, we formally test for the effect of name changes on the degree of inaccuracy of a fund by repeating the panel regression (4.3), including a name change dummy. We define the variable $\textit{Name Change}_t$, when the name of a fund in quarter t is different from its name in quarter $t-1$. Table 4.8 reports the effect of a name change on the degree of inaccuracy of a fund. The results in specifications (1) to (4) of Table 4.8 show across all subsamples that a name change in the quarter before does not significantly affect a fund's inaccuracy. More precisely, we find a positive but non-significant effect.

Many of those fund name changes are, however, not *meaningful* in our context. More precisely, the new name and the old name do not differ in terms of the mentioned investment styles (small, large, value, or growth). Therefore, in the next step, we differentiate between *non-meaningful* and *meaningful* fund name changes – changes in the name that refer to a change in the indicated style, e.g., from or to growth/value/small/large. There are 49 *meaningful* name changes in our sample (see Figure 4.4 in the Appendix for an overview over time).

Hence, the specifications (5) to (8) in Table 4.8 show the results when we control for the *meaningful* name changes. Contrary to the findings before, we document that when we control for meaningful fund name changes, a negative effect on the fund's degree of

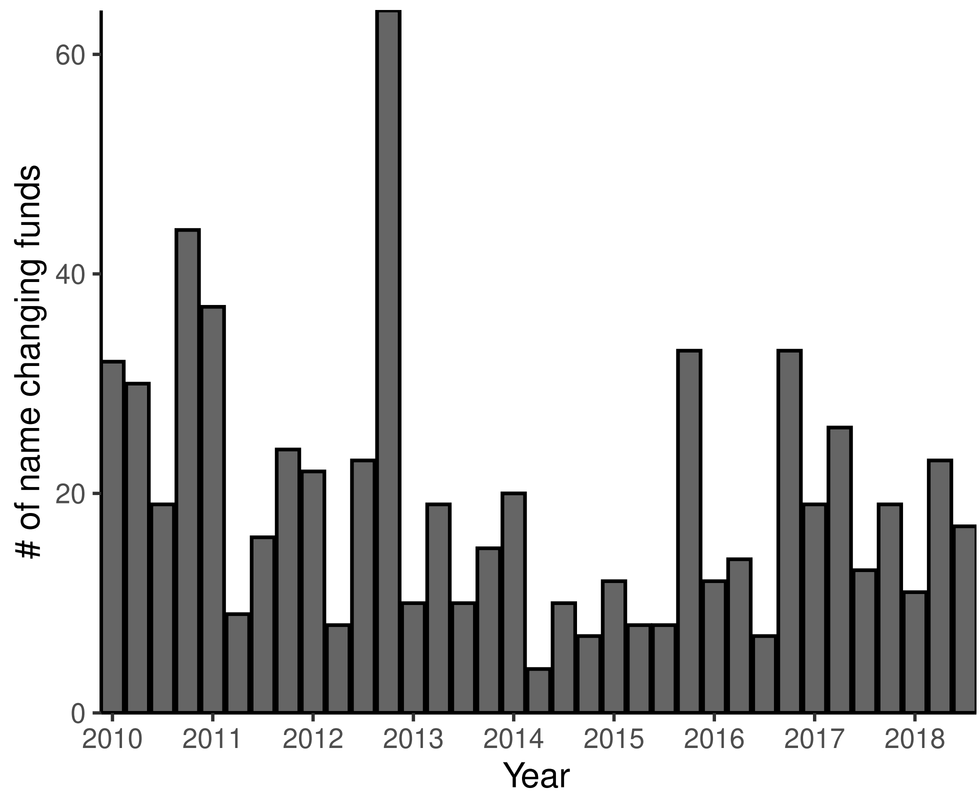


Figure 4.3: **Frequency of fund name changes**

Figure 4.3 shows the number of fund name changes for each quarter between 2010 and 2018. In total there are 665 fund name changes in our sample.

inaccuracy is significant at the 1% level in the SMB dimension. These results indicate that *meaningful* fund name changes are used as an instrument to bring fund names and the corresponding underlying portfolio again align with each other. Thus, fund name changes are also used to ensure that fund names provide accurate information.

Table 4.8: **Name changes and the inaccuracy of fund names**

Table 4.8 reports the result of a panel regression investigating the determinants of the degree of inaccuracy of a fund (i.e., the degree to which a fund deviates from the investment style stated in its name), including a name change dummy. The samples are as defined in Table 4.12. Quarter fixed effects are used. The dependent variable *Inaccuracy* is between 0 and 100. The independent variables are all standardized. The determinants are defined in Table 4.14. Columns (1) and (5) report the results for the whole sample of funds, columns (2) and (6) report the results for funds with a name related to the SMB dimension, columns (3) and (7) report the results for funds with a name related to the HML dimension, and columns (4) and (8) report the results for funds with a name related to both the SMB and HML dimensions. The standard errors are clustered at the fund level and are reported in parentheses. * , **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) All	(2) SMB	(3) HML	(4) SMB & HML	(5) All	(6) SMB	(7) HML	(8) SMB & HML
Name Change$_{t-1}$	0.1413	0.2156	0.1617	0.0988	0.1670	0.2783**	0.1639	0.1420
	(0.1459)	(0.1332)	(0.1763)	(0.1271)	(0.1496)	(0.1399)	(0.1789)	(0.1317)
Meaningful Change$_{t-1}$					-0.1021	-0.2439***	-0.0092	-0.1938***
					(0.1539)	(0.0412)	(0.2180)	(0.0436)
Rank$_{[t-3,t-1]}$	-0.6591***	-0.4708***	-0.8455***	-0.3451**	-0.6578***	-0.4677***	-0.8454***	-0.3433**
	(0.1871)	(0.1644)	(0.2172)	(0.1687)	(0.1871)	(0.1645)	(0.2171)	(0.1688)
Fund Flow$_{t-1}$	0.2176	0.0481	0.3551*	0.0934	0.2204	0.0575	0.3553*	0.1007
	(0.1703)	(0.1517)	(0.2043)	(0.1562)	(0.1702)	(0.1513)	(0.2042)	(0.1560)
Mean Flow$_{[t-3,t-1]}$	-1.0253***	-0.6357***	-0.6947***	-0.2112	-1.0267***	-0.6399***	-0.6948***	-0.2167
	(0.2036)	(0.1747)	(0.2444)	(0.1999)	(0.2036)	(0.1740)	(0.2444)	(0.2000)
Risk$_{t-1}$	0.5606***	0.6170***	0.4031*	0.4365**	0.5606***	0.6164***	0.4031*	0.4362**
	(0.1891)	(0.1648)	(0.2101)	(0.1812)	(0.1891)	(0.1649)	(0.2101)	(0.1812)
Fund Size$_{t-1}$	-0.0290	-0.0623	-0.0452	-0.1149	-0.0283	-0.0622	-0.0451	-0.1135
	(0.3619)	(0.3178)	(0.3990)	(0.3152)	(0.3618)	(0.3177)	(0.3990)	(0.3151)
log(Age)$_{t-1}$	0.3222	0.1675	0.2451	0.0477	0.3217	0.1653	0.2450	0.0435
	(0.2823)	(0.2233)	(0.3090)	(0.2229)	(0.2823)	(0.2233)	(0.3090)	(0.2229)
Expense ratio$_{t-1}$	1.8404***	0.4824	2.6350***	0.7274**	1.8404***	0.4813	2.6350***	0.7248**
	(0.3639)	(0.3099)	(0.3714)	(0.3002)	(0.3640)	(0.3097)	(0.3714)	(0.3003)
Turnover$_{t-1}$	0.1300	0.1907	-0.1014	0.0717	0.1298	0.1909	-0.1014	0.0729
	(0.2959)	(0.2059)	(0.3436)	(0.2754)	(0.2959)	(0.2059)	(0.3436)	(0.2751)
Quarter Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
Observations	19,662	10,466	15,055	5,937	19,662	10,466	15,055	5,937
Adj. R^2	0.0753	0.0622	0.0693	0.0564	0.0753	0.0621	0.0693	0.0564

4.6 Consequences of Inaccurate Names

Finally, we analyze the possible consequences of deviating from the investment style stated in the name. In particular, we are interested in central fund characteristics before and after a name becomes inaccurate. Our goal is to investigate whether implementing a deviation strategy to achieve a higher performance ranking is effective and to understand the investors' reaction to an inaccurate name.

Given that deviating from the stated investment style is not random, we follow Cooper et al. (2005) and rely on propensity score matching. This approach allows us to match funds similar in every characteristic but the naming accuracy. To obtain the propensity score, we estimate a logit regression using the same explanatory variables as in Table 4.5. Moreover, to ensure that we match funds that are as similar as possible and to control for unobservable characteristics across time, we restrict ourselves to matches of funds within a year-quarter-style category, where style is either related to the SMB dimension, to the HML dimension, or to both dimensions at the same time. Once a match is found, we compute *abnormal* fund characteristics as the difference between the characteristics of the treated fund (whose name switches from accurate to inaccurate) and of the control fund (whose name keeps being accurate).

The results are reported in Table 4.9. They are reported for each dimension on which a fund name can be inaccurate (only SMB, only HML, or both). Moreover, given the results of the previous section highlighting that funds having an inaccurate name for one quarter are not the same as funds having an inaccurate name for more than one quarter, we report three different results: (1) using the full sample of inaccurate fund names ($N >= 1$), (2) using a sample of funds whose names are only inaccurate for one quarter ($N = 1$), (3) and using a sample of funds whose names are inaccurate for more than a quarter ($N > 1$).

Our first characteristic of interest is fund flows, as those indicate whether and how investors react to such name inaccuracy. An increase in fund flows could be interpreted as an increased interest in the fund from investors. The increased fund flow also means that managers receive higher compensation (managers' compensation is increasing with the fund's size). On the other hand, a decrease in fund flows could indicate that investors take note of funds' deviating behavior and decide to invest in alternative products.

Overall, Panel A in Table 4.9 shows that funds do not experience statistically significant abnormal outflows. This result, therefore, suggests that investors do not respond to inaccurate information. Moreover, while the ultimate goal of the deviation strategy implemented by fund managers is to attract new investments into the funds in order to increase their compensation, the results show that this is not effective, on average.

Second, we examine potential consequences in a funds' return rank. If the deviation from the stated investment strategy leads to a higher rank, this indicates that the strategy to use deviations to increase the fund rank is successful. However, we do not find evidence that such deviating behaviour consistently pays off in terms of improving the fund's performance rank. The strategy sometimes even negatively impacts the rank. In this case, not deviating from the name-suggested style would have delivered better relative performance.

Panel B in Table 4.9 also reports a significant difference in abnormal ranks depending on whether funds deviate on the SMB dimension or on the HML dimension. While fewer funds are deviating on the SMB dimension, these results suggest that those funds which deviate do this in a rather extreme manner. Given that the SMB dimension is more strictly regulated than the HML dimension, these results suggest that the stricter name regulation is not effective in reducing the severity of such deviations, even if it is effective in reducing the occurrence of inaccurate names (as shown in Table 4.3).

It is also interesting to note that the SMB funds do not suffer from significant outflows of money despite their worse performance ranking. This finding can be explained by the asymmetric relationship between flows and returns (Brown et al., 1996; Chevalier and Ellison, 1997).

Third, we investigate the consequence in terms of risk. A higher risk would highlight that the funds "gamble" by deviating to try to achieve a better ranking. Moreover, if risk increases and the rank is not improved, investors do not benefit from a fund's decision to deviate from its stated investment style. Bearing higher risk but not benefiting in terms of returns is clearly undesirable for investors.

The results of abnormal risk reported in Table 4.9 show that risk significantly increases. This result, taken together with the abnormal rank results, shows that a fund's risk/return trade-off is worse after a deviation. Again, we observe a significant difference between funds that deviate on the SMB dimension and those who deviate on the HML dimension: the trade-off is even worse for those deviating on the more strictly regulated SMB dimension.

In general, the results reported in Table 4.9 highlight that funds perform very poorly after deviating from the investment style stated in their name. This suggests that these funds gambled but lose. Hence, our findings are in line with the tournament hypothesis.

Moreover, as highlighted by the absence of abnormal flows, investors are not able to

Table 4.9: **Abnormal Characteristics**

Table 4.9 reports abnormal characteristics of funds following a name inaccuracy. In order to compute these abnormal characteristics, a propensity score matching technique is used to find a fund with an accurate name which is the most closely related to a fund with an inaccurate name. The propensity score are obtained with a logit regression using as dependent variable a dummy that is equal to 1 when the fund name becomes inaccurate and 0 when the fund name remains accurate. The explanatory variables are the same as in Table 4.5. The control fund is also required to be in the same year-quarter-style category as the treated fund, where style is either related to the SMB dimension, to the HML dimension, or to both dimensions at the same time. The abnormal characteristic is the difference between the characteristic of the treated fund and the characteristic of the control fund. Panel A reports the abnormal characteristics and whether they are significantly different from zero. Panel B reports the difference in abnormal characteristics, depending on the dimension present in the fund name (SMB, HML, or both). The results are also split for different samples: $N >= 1$ is a sample of funds whose names are inaccurate for at least one quarter, $N = 1$ is the sample of funds whose names are inaccurate for exactly one quarter, and $N > 1$ is the sample of funds whose names are inaccurate for more than one quarter. * , **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) Flow	(2) Rank	(3) Risk
Panel A: Abnormal characteristics			
All			
(1a) N>= 1	-0.6399	-0.0264**	0.3562***
(1b) N= 1	-2.3534*	-0.0136	0.7608***
(1c) N> 1	-0.4290	-0.0280**	0.3064***
SMB			
(2a) N>= 1	-0.4196	-0.0732**	0.7686***
(2b) N= 1	-3.2930	-0.0455	0.9826***
(2c) N> 1	0.6066	-0.0832**	0.6922***
HML			
(3a) N>= 1	-0.5971	-0.0172	0.2635***
(3b) N= 1	-1.7431	0.0040	0.6457***
(3c) N> 1	-0.4975	-0.0191	0.2303***
SMB & HML			
(4a) N>= 1	-2.8948*	-0.0527	0.9052***
(4b) N= 1	-3.1405	-0.0034	0.5897
(4c) N> 1	-2.8411	-0.0635	0.9742***

Table 4.9 continued.

Panel B: Within-sample comparison

SMB vs. HML			
T-stat (2a)-(3a)	0.1611	-1.8008*	4.9297***
T-stat (2b)-(3b)	-0.5460	-0.6897	1.6493
T-stat (2c)-(3c)	0.9981	-1.8327 *	3.7180***
SMB & HML vs. SMB			
T-stat (4a)-(2a)	-1.3949	0.2814	0.5111
T-stat (4b)-(2b)	0.0386	0.3219	-1.0006
T-stat (4c)-(2c)	-1.7638*	0.2317	0.8898
SMB & HML vs. HML			
T-stat (4a)-(3a)	-1.4500	-0.5214	2.5652**
T-stat (4b)-(3b)	-0.4174	-0.0608	-0.1460
T-stat (4c)-(3c)	-1.2999	-0.5608	2.5261**

notice this deviation, at least not in a timely manner. This adds an additional layer of concern: investors are worse off but do not react. Thus, our results highlight the need for stricter regulations, not only when a fund changes its name or is created but also over its whole life cycle.

4.7 Conclusion

A significant fraction of mutual funds refers to an investment style in their name. This paper explores whether these funds stick to these highlighted investment styles or deviate from it, resulting in inaccurate fund names. In particular, we want to understand which funds provide inaccurate name information, why they feature an inaccurate name and the consequences of such inaccuracy.

To answer these research questions, we construct a fund name history dataset based on fund prospectuses in the EDGAR database of the SEC. Extracting information from more than 400,000 prospectuses between January 2010 and December 2018 allows us to build a detailed name history dataset for U.S. equity mutual funds. To identify inaccurate fund names, we then use a cluster analysis technique.

In the first part of the paper, we document that a significant fraction of mutual funds is associated with an inaccurate fund name. We find that 33% of U.S. equity mutual funds have an inaccurate name at least once in their life-cycle. Second, we focus on two specific dimensions on which a name can be inaccurate: the size dimension (name including the terms *small* or *large*), and the investment strategy dimension (name including the terms *growth* or *value*). The size dimension displays relatively few inaccurate fund names, while inaccurate fund names are abundant in the investment strategy dimension. This result is not surprising given that the SEC regulates more strictly the names related to the size dimension (see Rule 35d-1) than those related to the investment strategy dimension.

Regarding the characteristics of funds with inaccurate fund names, we find that funds that deviate from the investment style stated in their names experience lower fund inflows, are riskier, and charge higher expense ratios. More importantly, we find that funds that are relative losers in performance compared to their competitors deviate more from the stated investment styles in the names. This finding can be rationalized by prospect theory and supports our tournament hypothesis, which states that funds deliberately use deviations from the style in the name as a strategy to climb the performance ranking. This hypothesis is further supported by the fact that we do not observe such an effect for funds, which only have an inaccurate name for one quarter (which could be more the result of inattention than strategy).

Finally, to shed light on the consequences of inaccurate fund names, we estimate potential abnormal characteristics of inaccurate funds with respect to funds that do not deviate from the investment style included in their name. We rely on propensity score matching to overcome potential endogeneity problems. By looking at funds' performance ranking and idiosyncratic risk, respectively, we find that funds do not improve their ranking while being exposed to higher idiosyncratic risk after deviating from the stated investment style. This consequence is even more pronounced for funds whose name is more strictly regulated by the SEC. However, investors fail to actively respond to these disadvantageous characteristics of funds having an inaccurate name as we do not document any significant abnormal fund outflows.

Overall, our results highlight the role of transparency and a precise regulation in the fund names.

A.4 Additional Figures and Tables

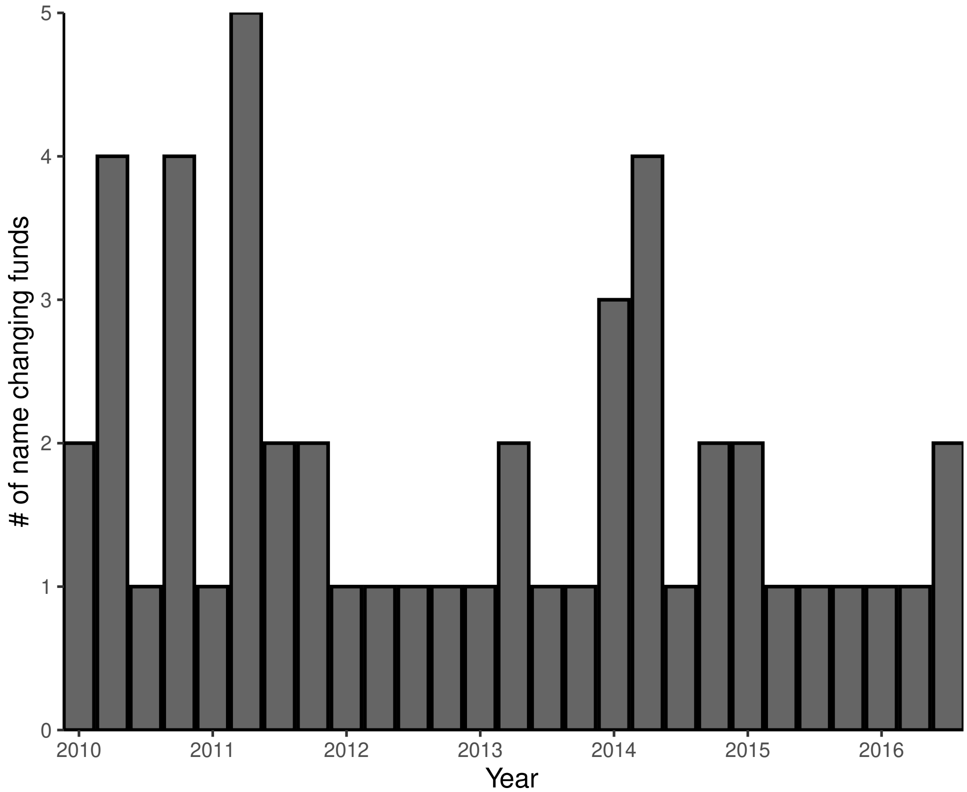


Figure 4.4: **Frequency of non-cosmetic fund name changes**

Figure 4.4 shows the number of fund name changes for each quarter between 2010 and 2018. In total there are 49 fund name changes in our sample.

Table 4.10: **Prospectus data**

Table 4.10 shows the number of prospectuses for each form type that mutual funds have to fill and whether the information is already at the fund level or the fund family level. 497, 497K, 485APOS, and 485BPOS filings are available in the EDGAR SEC database. In total, we retrieve fund names from 418,938 prospectuses, covering 20,973 funds (SeriesId's). Prospectus data is provided in the eXtensible Business Reporting Language (XBRL) format. The fund name in a prospectus can be identified due to the XBRL tree and key structure. We extract for all prospectuses the most recent name on a fund for each fund and month-year. Merging the data with the Morningstar database via the share class ticker symbol and restricting the sample to equity funds only results in 2,166 funds between 2010 and 2018.

Prospectus type	# of observations	Fund level
497	164,654	Yes
497K	168,409	Yes
485APOS	12,586	No
485BPOS	73,289	No
Total	418,938	

Table 4.11: **Possible cases of inaccurate names**

Table 4.11 shows the eight possible cases that we have in our sample and the associated number of fund-quarter observations. A fund name either refers to the SMB dimension (*small* or *large*), to the HML dimension (*value* or *growth*), or to both dimensions. When a fund name refers to both dimensions, it can be inaccurate (or accurate) on only one of these two dimensions, or on both.

	Name	SMB dimension	HML dimension	N
(1)	SMB	Accurate		5513
(2)	SMB	Inaccurate		135
(3)	HML		Accurate	10,752
(4)	HML		Inaccurate	1961
(5)	SMB & HML	Accurate	Accurate	7729
(6)	SMB & HML	Inaccurate	Accurate	116
(7)	SMB & HML	Accurate	Inaccurate	748
(8)	SMB & HML	Inaccurate	Inaccurate	48

Table 4.12: **Control and treatment groups**

Table 4.12 shows the number of fund-quarter observations during which a name switches from being accurate to being inaccurate (columns *Treated*) or remains accurate (columns *Control*). The numbers are reported per type of name and per dimension on which a name is inaccurate. We obtain three different treatment and control groups, one for each dimension on which a fund name can be inaccurate. SMB refers fund-quarter observations associated to cases (1), (2), (5), and (6) in Table 4.11. The fund names in the treatment group switch from being part of the accurate name group (1)+(5) to being part of the inaccurate name group (2)+(6), while fund names in the control group remain in group (1)+(5). HML refers to fund-quarter observations represented by cases (3), (4), (5), and (7). The fund names in the treatment group switch from being part of the accurate name group (3)+(5) to being part of the inaccurate name group (4)+(7), while the fund names in the control group remain in group (3)+(5). SMB & HML refers to fund-quarter observations of cases (5) and (8). The fund names in the treatment group switch from being part of the accurate name group (5) to being part of the inaccurate name group (8), while the fund names in the control group remain in group (5). Note that, when a name includes both dimensions and remains accurate on both, the associated fund-quarter observation is included in the SMB control group, in the HML control group, and in the SMB & HML control group.

	SMB		HML		SMB & HML	
	Control	Treated	Control	Treated	Control	Treated
Small	3876	100				
Small & Growth	1299	28	1299	224	1299	4
Small & Value	2496	42	2496	56	2496	16
Large	1524	14				
Large & Growth	1696	17	1696	43	1696	18
Large & Value	1661	15	1661	77	1661	3
Growth			5323	576		
Value			4448	379		

Table 4.13: **Characteristics of treatment vs control**

Table 4.13 reports the summary statistics of funds in the *treatment* group, defined as funds which have an inaccurate name in quarter t while having an accurate name in quarter $t-1$. These funds are compared with funds in the *control* group, which are those having an accurate name in both quarters t and $t-1$. The last two columns present the difference and the statistics of a two-sided t-test for significant differences. The sample includes all equity U.S. mutual funds in the Morningstar database that are linked to a name in the SEC database and have a name referring to the SMB dimension (*small* or *large*), to the HML dimension (*value* or *growth*), or to both. This results in 22,323 accurate and 1,612 inaccurate fund-quarter observations between 2010 and 2018, removing any missing observations in the characteristics. * , ** , and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Control			Treatment				
Variable	Mean	Median	Std	Mean	Median	Std	Diff	t-stat
Fund Flow (in %)	2.07	0.52	14.06	1.33	0.02	13.87	0.75	2.05*
log(Fund Size (in mn. $)	19.48	19.62	2.01	19.17	19.22	2.01	0.31	6.02***
log(Company Size)	21.91	22.12	2.02	21.43	21.75	2.01	0.48	9.20***
Age (in Years)	14.93	13.83	10.39	15.41	14.08	10.75	-0.48	-1.80*
Return (in %)	1.15	1.12	5.10	1.38	1.40	5.08	-0.23	-1.76
Risk (in %)	0.32	0.21	0.43	0.83	0.36	1.00	-0.51	-40.43***
Expense Ratio (in %)	0.11	0.09	0.09	0.13	0.11	0.10	-0.02	-8.01***
Turnover Ratio (in %)	71.33	52.00	88.11	74.22	52.03	90.71	-2.88	-1.26
Cash (in %)	2.53	1.74	6.65	3.12	1.95	6.67	-0.59	-3.41***
FI (in %)	0.28	0.00	4.89	0.28	0.00	4.3	-0.01	-0.06
Equity (in %)	96.78	97.91	5.33	96.00	97.57	6.91	0.78	5.51***

Table 4.14: **Variable definitions**

Table 4.14 provides definitions of all variables used in this paper. MS indicates Morningstar, C refers to own calculation and SEC indicates data from the Securities and Exchange Commission.

Variable name	Description	Source
Name	Name history of the fund as extracted from all prospectus fillings in EDGAR	SEC
Series ID	Fund identifier as extracted from the prospectuses in EDGAR	SEC
Fund Flow (in %)	Computed as $(TNA_{f,t} - TNA_{f,t-1}(1 + RF_{f,t}))/(TNA_{f,t-1}(1 + RF_{f,t}))$, where $TNA_{f,t}$ corresponds to fund f's total net assets (TNA) in quarter t and $RT_{f,t}$ denotes fund f's return in quarter t. The variable is winsorized at the 1st and 99th percentile.	MS, C
Mean Flow$_{[t-3,t-1]}$ (in %)	Average flow over the 3 quarters before the observation quarter t.	MS,C
Return (in %)	Quarterly log-return computed as the sum of monthly log-returns. Monthly returns are computed as the percentage return calculated as the change in monthly net asset value minus management fees and other regular costs.	MS, C
Rank (in %)	Rank of the fund return in comparison to funds having the same terms in their names. Fund return is the quarterly log-return.	MS, C
Rank$_{[t-3,t-1]}$ (in %)	Rank of the fund return in comparison to funds having the same terms in their names. Fund return is computed as the log-return over the 3 quarters (9 months) before the observation quarter t	MS, C
Risk (in %)	Standard deviation of the residuals from a model including the three Fama and French factor returns as well as the Carhart momentum factor. Factor returns are from Kenneth French's library. It is expressed in %.	MS, C
Fund Size	Logarithm of fund's quarterly total net assets in million USD, aggregated at the fund level.	MS, C
Company Size	Logarithm of company's quarterly total net assets in million USD, aggregated at the investment company level.	MS, C
Age (in Years)	Fund's age computed as the difference from quarter t to the inception date of the oldest share class.	MS, C

Variable definitions, Table 4.14 continued

Variable name	Description	Source
log(Age (in Years))	Logarithm of fund's age in months computed as the difference from quarter t to the inception date of the oldest share class.	MS, C
Expense Ratio (in %)	Fund's quarterly expense ratio expressed in percent.	MS
Turnover (in %)	Fund's quarterly turnover ratio expressed in percent.	MS
Inaccurate	Classification of fund's name as accurate (0) or inaccurate (1) based on the Fuzzy C-means clustering method in quarter t.	C
Inaccuracy (in %)	Degree of inaccuracy of the fund's name in percent. When a fund is inaccurate in two different dimensions, the maximum inaccuracy across the two dimensions is used.	C
SMB	Size factor in the Carhart four factor regression.	C
HML	Book-to-market factor in the Carhart four factor regression.	C
Cash Proportion	The percentage of the fund's net assets in cash.	MS
FI Proportion	The percentage of the fund's net assets in fixed income.	MS
Equity Proportion	The percentage of the fund's net assets in equity.	MS
Holdings	Quarterly number of holdings that are in the portfolio of a fund.	MS
Name Change	A dummy that indicates for each fund quarter observation a fund name change (1) or not (0)	SEC, C
Non-Cosmetic Change	A dummy that indicates for each fund name change whether it is non-cosmetic (1) or cosmetic (0)	SEC, C

Part III

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Part IV

Curriculum Vitae

Curriculum Vitae

Personal Details

Name:	Nils Jonathan Krakow
Date of birth:	13 May 1990
Nationality:	German

Education

09/2016 – 04/2021	**PhD studies in Banking and Finance** University of Zurich, Switzerland Supervisor: Prof. Dr. Marc Chesney 08/2019 – 10/2019: Visiting PhD student Melbourne University, Australia
09/2013 – 07/2016	**Master of Arts in Economics** University of Zurich, Switzerland 02/2015 – 07/2015: Exchange student University of Copenhagen, Denmark
09/2010 – 09/2013	**Bachelor of Arts in Economics** University of Zurich, Switzerland

Professional Experience

02/2016 – today	Teaching and research assistant Chair of Quantitative Finance, University of Zurich
08/2012 – 02/2017	Teaching assistant Department of Economics, University of Zurich
02/2014 – 08/2014	Internship at Credit Suisse Swiss Institutional Credit Research
08/2009 – 03/2010	Civil Service at Neukirchener Erziehungsverein