Essays in Empirical Finance

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The President:

Prof. Dr. Thomas Bieger

Dedicated to my family for their endless love, support, and encouragement

Summary

This dissertation consists of three independent papers.

The first paper investigates the role of incomplete investor information in financial innovations. We analyze the information that structured product issuers provide to the investors and find that issuers have an information advantage over investors regarding two important valuation parameters: volatility and dividends. This advantage allows issuers to push overpriced securities to investors and induces them to design products with large information frictions. The insights are of systemic importance because they suggest that product issuers' behavior increases information frictions in the financial system.

The second paper examines the role of obfuscation in the market for structured products. By exploiting the staggered adoption of a price disclosure policy, I show that issuers subject to price disclosure significantly increase the complexity of their products. Further, I provide evidence that complexity significantly reduces the price elasticity of demand, thus raising the concern that complexity induces social welfare costs.

The third paper proposes an explanation for the empirically documented relation between the value factor and the investment factor of the Fama-French five-factor model: Investors observing that a firm decreases its investment perceive the firm as riskier, and therefore adjust their valuations of the firm downwards. Consequently, the firm's book-to-market ratio increases. In support of this conjecture, we find considerable overlap between the factor-mimicking portfolios of the value and the investment factor. We show that this overlap is driven by stocks that experience an increase in their book-to-market ratios due to a decrease in their market values. Moreover, our results show that these value stocks behave like low investment stocks and thus earn a premium. Together with actual low investment stocks, these stocks are primarily responsible for the value premium.

Zusammenfassung

Die vorliegende Dissertation besteht aus drei unabhängigen Studien.

Die erste Studie untersucht die Rolle von Informationsfriktionen von Investoren im Markt für Finanzinnovationen. Wir zeigen, dass Emittenten von strukturierten Produkte gegenüber Investoren insbesondere bezüglich zwei Parametern über einen Informationsvorteil verfügen: Volatilität und Dividenden. Diesen Vorteil ermöglicht es Emittenten überteuerte Produkte zu verkaufen und verleitet sie dazu die Produkte zu ihren Gunsten zu gestalten. Diese Erkenntnisse sind wichtig, weil dieses Verhalten der Emittenten zu noch grösseren Informationsfriktionen führen kann.

Die zweite Studie untersucht die Rolle von Verschleierungstaktiken im Markt für strukturierte Produkte. Anhand einer zu verschiedenen Zeitpunkten adaptierten Preistransparenzrichtlinie zeige ich, dass Emittenten die Komplexität ihrer Produkte erhöhen sobald sie anfangen die Preise auszuweisen. Zudem zeige ich, dass Komplexität zu einer reduzierten Preissensitivität der Investoren führt. Diese Erkenntnisse sind wichtig, weil sie auf eine Verschlechterung der sozialen Wohlfahrt aufgrund von Komplexität hindeuten.

Die dritte Studie liefert eine Erklärung für den starken Zusammenhang zwischen dem Value- und dem Investment Faktor im Fama-French-Fünffaktormodell: Investoren, welche eine Reduktion der Investitionen einer Firma feststellen, nehmen diese als riskanter wahr und passen den Marktwert der Firma nach unten an. Als Folge davon erhöht sich das Buchwert-Kurs-Verhältnis. Wir finden eine grosse Überschneidung zwischen den Factor-Mimicking Portfolios des Values- und Investmentfaktors. Zudem zeigen wir, dass diese Überschneidung vor allem durch Aktien getrieben wird, für welche die Buchwert-Kurs-Verhältnisse angestiegen sind, weil ihre Marktwerte gesunken sind. Diese Aktien verhalten sich wie Aktien mit tiefen Investitionen und erzielen eine Prämie. Zusammen mit Aktien, welche tatsächlich über tiefe Investitionen verfügen, treiben diese die Value Prämie.

Illuminating the Dark Side of Financial Innovation: The Role of Investor Information*

Manuel Ammann[†], Marc Arnold[‡], and Simon Straumann[§]

Abstract

This paper investigates the role of incomplete investor information in financial innovations. By analyzing the information that structured product issuers provide to the investors of those products, we find that issuers have an information advantage over investors regarding two important valuation parameters: volatility and dividends. This advantage allows issuers to push overpriced securities to investors and induces them to design products with large information frictions. We confirm our conjecture that issuers exploit their superior information in a regression discontinuity design. The results are of systemic importance because they suggest that product issuers' behavior increases information frictions in the financial system.

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1 Introduction

Retail investors make investment mistakes in the financial innovation market that have large welfare costs (Shiller, 2003). One driver of this dark side of financial innovation, incomplete investor information, has attracted particular attention since the 2007–2008 financial crisis because information frictions can cause dramatic market disruptions (Gennaioli, Shleifer, and Vishny, 2012; Hanson and Sunderam, 2013). Information disclosure is, therefore, at the forefront of the current regulatory efforts to improve financial market stability and increase welfare. In his presidential address, Campbell (2006) stressed that such disclosure regulations can reduce investment mistakes if they are appropriately designed. However, an appropriate design requires a deep understanding of the role of incomplete investor information in financial innovations. Yet, relatively little is known about this role due to two main challenges. First, information sets are usually not observable, making it hard to measure incomplete information. Second, it is difficult to isolate the role of incomplete information from that of other frictions such as investors' limited financial literacy that is discussed in Henderson and Pearson (2011).

This study investigates the role of incomplete investor information in the financial innovation market. We overcome the challenges of analyzing this role through our access to a comprehensive database of structured products and by using a regression discontinuity design (RDD). Specifically, the database solves the information-observability challenge because it contains the information that structured product issuers provide to a product's investors. The RDD addresses the identification challenge by exploiting a discontinuity in incomplete investor information.

Our analysis provides three primary results. First, product issuers' information advantage over retail investors plays a key role in explaining the overpricing of structured products. Second, the specific sources of this information advantage are volatility and dividends. Third, issuers design products towards this information advantage. The first result implies that information frictions are important besides limited financial literacy to explain the investor mistakes in the financial innovation market. This distinction is crucial to an appropriate regulatory design that aims to reduce investment mistakes. Specifically, information frictions call for disclosure, whereas limited financial literacy evokes more comprehensive regulatory measures such as the expansion of financial education or product-selling restrictions. Our second result helps policymakers to evaluate and incorporate the finding in the disclosure literature that publicly disclosing more information can benefit or harm welfare (Bond and Goldstein, 2015; Goldstein and Yang, 2019) depending on the type of information. The third result is of systemic importance because it underpins the concern that financial engineering causes investor information frictions in financial markets.

The database contains the term sheets of all structured products on single-stock underlyings issued in Switzerland. This database represents an ideal laboratory to explore the role of incomplete information in financial innovations for several reasons. First, structured products in Switzerland are frequently issued to retail investors (SSPA, Swiss Structured Products Association, 2013). This clientele usually has inferior information compared to that held by financial intermediaries (Bhattacharya et al., 2012). Second, the Swiss regulator prescribes the information that structured product issuers must provide to investors in detail (e.g., Swiss Bankers Association, 2007). This standardization allows us to derive proxies of issuers' information advantage. Third, the database contains all publicly issued products in Switzerland, reducing selection bias concerns. Finally, issuers have considerable flexibility to tailor these products (Henderson and Pearson, 2011; Célérier and Vallée, 2017), which enables us to analyze the impact of their information advantage on product design.

The market for structured products is well established in Europe and has, according to the SEC database, grown substantially in the US in recent years (Bouveret et al., 2013). Thus, structured products represent an important segment of the financial innovation market. For the products in our sample, we calculate the percentage difference between product issue prices to retail investors and replication prices for identical payout profiles to institutional investors. We label this difference the markup ($Markup$) and use it to measure product overpricing. Analyzing price differences helps isolate the impact of the information friction on overpricing because price determinants that are not associated with market frictions affect both the issue and replication prices, but not their difference.

We start by analyzing the information content of the structured products' term sheets. Issuers are obliged to disclose important product information to investors on these sheets. We find that the missing pieces of information on the term sheets to assess the replication price of structured products are volatility and the dividends of the products' underlyings. The large financial institutions that issue these products have an information advantage on these parameters because they can access the implied volatilities and forecasted dividends from databases such as EUREX and IBES. Those databases are disproportionately costly to retail investors, causing information frictions that leave investors incompletely informed. We then show that product overpricing increases with volatility and dividends. As the replication prices in our sample decline with volatility and dividends, this result suggests that issuers exploit their information advantage. We apply a battery of tests to confirm this information hypothesis and to exclude alternative explanations for our results such as the financial literacy hypothesis. The later suggests that investors simply lack the financial sophistication to recognize that higher volatility and dividends reduce product replication prices (Henderson and Pearson, 2011).

First, we incorporate proxies of investors' volatility and dividend information. Because retail investors commonly refer to publicly available historical information, we use historical volatility and dividends (Daniel et al., 2002; Sirri and Tufano, 1998). We find that issuers earn a 68% (101 basis points) larger $Markup$ with products for which implied volatility is higher than historical volatility. Similarly, they earn a 52% (77 bps) higher $Markup$ with product underlyings for which analysts forecast a higher dividend than the historical dividend. These results confirm that issuers overprice products when they have an information advantage, i.e., they do so when investors underestimate the relevant volatility or dividend based on historical information and thus overestimate a product's value. We also show that issuers' tendency to exploit this information channel is stronger when the products' value-sensitivity to the information advantage is larger and the portion of retail investors is higher.

Second, the effect that $Markup$s are higher when implied volatility is larger than historical volatility is weaker for underlyings with publicly available implied volatility estimates.

Finally, we investigate how issuers design structured products. We find that they select underlying stocks with a higher implied than historical volatility and with a higher forecasted than historical dividend to structure the products. The results suggest that issuers try to exploit investors by designing the products towards their information advantage. This design behavior raises the concern that financial innovators aggravate investor information frictions in financial markets.

Although we take care to consider price differentials, relevant controls, robustness tests, and refinements to exclude alternative explanations of our regression results, it is challenging to establish a causal relationship between incomplete investor information and security overpricing because it is difficult to isolate differences in issuers' information advantage that are independent of product, macroeconomic, or issuer characteristics, as well as investors' financial literacy. We address this identification problem by exploiting a discontinuity in issuers' information advantage. Specifically, while access to analyst forecasts gives issuers a dividend information advantage over investors, this advantage declines once the dividend of a product's underlying is publicly announced. Thus, we compare the $Markup$s of products with a dividend information advantage issued just before the dividend announcement date to the $Markup$s of products issued just after the dividend announcement date in a standard RDD setting. We find that the former have a discontinuously larger $Markup$ than the latter. Thus, the RDD test confirms that issuers' information advantage allows them to sell overpriced securities to investors. It is hard to reconcile this result with the financial sophistication hypothesis because it is unlikely that investors' sophistication level features a discontinuity at dividend announcement dates.

The incomplete information hypotheses that we postulate only imposes relatively limited requirements on investors' financial sophistication. Specifically, the term sheets allow investors to perform a model-free rank ordering of the structured products by comparing the products' key terms even if the investors lack the ability to actually price these products.[1] For example, investors are likely to recognize that a product with a larger coupon is more attractive than a comparable product with a lower coupon without applying a pricing model. Indeed, Egan (2019) argues that a rank ordering is much simpler for structured products than for other financial products such as mutual funds because structured products are completely characterized by a small number of dimensions. This comparability among competing products reduces the issuers' opportunity to exploit investors. The simple comparison argument, however, only holds for the product terms that are disclosed on a term sheet. Thus, our incomplete information story relies on the premise that issuers can exploit their volatility and dividend information because that information is not disclosed on the term sheets, which prevents investors from undertaking the model-free rank ordering along these dimensions. Campbell (2006) highlights that many households find solutions to relatively complex investment problems. Thus, it is very plausible that at least some investors can rank order competing products along the dimensions underlying risk or dividend if they have that information.

Our results contribute to two streams of the literature. The first stream analyzes the reasons behind investors' mistakes in the financial innovation market (DeMarzo, 2005; Coval et al., 2009; Choi et al., 2009; Carlin, 2009; Carlin and Manso, 2010; Henderson and Pearson, 2011; Célérier and Vallée, 2017; Chang et al., 2015; Li et al., 2018; Egan, 2019). This literature agrees that retail investors buy overpriced securities from financial

[1] Search costs for investors are relatively small as the term sheets of outstanding products and products in subscription are readily available form the issuers' home page.

innovators. It shows that investors' bias, ignorance of fees, and lack of financial sophistication, as well as product complexity, obfuscation, missing suitability checks, and the incentive asymmetry between investors and brokers can partially explain this investor mistake. We contribute to this literature by identifying investors' inferior access to financial information as an important additional explanation of retail investor mistakes. We thereby advance the idea that firms shroud some aspects of the terms on which they offer their products to exploit uninformed consumers (Gabaix and Laibson, 2006).

Second, we add to the literature that points to incomplete investor information as a crucial friction in the financial innovation market (Ashcraft and Schuermann, 2008; An et al., 2011). Gennaioli et al. (2012), Gorton and Metrick (2012), Stein (2012), and Hanson and Sunderam (2013) argue that this friction is risky for the entire financial system because it can cause large market disruptions when new information arrives. Despite this concern, surprisingly little is known about the sources of incomplete investor information in the financial innovation market. An exception is Piskorski et al. (2015), who find significant asset quality misrepresentation by issuers of residential Mortgage-Backed Securities. We contribute to this literature in two ways. First, we identify volatility and dividends as two important sources of the investor information friction. As the recent disclosure literature suggests that the type of information disclosed is key to determining whether disclosure is welfare improving (Bond and Goldstein, 2015; Goldstein and Yang, 2019), knowing the specific sources is crucial to guide policymakers in the discussion on how to regulate disclosure to mitigate the friction. Second, our results pertaining to the design of structured products emphasize a systemic stability concern. Specifically, they imply that financial innovators deliberately structure products for which investors have inferior information, thereby creating information frictions in the financial system.

2 Structured products: Market and data sample

Structured products are investment instruments with payoffs that are linked to the performance of one or several underlyings from a wide range of asset classes such as equity, fixed-income, and commodities. Structured products consist of multiple financial instruments, commonly a combination of bonds, equities and derivatives. Banks issue structured products to investors on the primary market. Investors can subsequently trade the products on the secondary market. In this study, we focus on the primary market, for two reasons. First, the secondary market is relatively illiquid and has a much lower trading volume than the primary market (SSPA, Swiss Structured Products Association, 2013). Second, we are also interested in the product design, which issuers determine at issuance.

The market for structured products has grown substantially. Bouveret et al. (2013) report a total outstanding volume of structured products in Europe of almost 770bn EUR as of December 2012. This notional volume amounts to 4% of household financial wealth, or 12% of mutual funds' assets under management in the European market. With a total sales volume of 21.3bn USD, Switzerland was the second largest European issuer of structured products in 2014 (Structured Retail Products, 2015). The Swiss market has also been the global leader in terms of the volume of structured products invested in custody accounts (Swiss Bankers Association, 2011). While the US structured product market traditionally lagged behind its European counterpart, it dramatically increased its volume in recent years. Specifically, the yearly US sales volume of publicly registered structured notes in the SEC database increased from 0.3bn USD in 2000 to 43.5bn USD in 2015. Most products have equity underlyings from both the US and Europe (Bloomberg Brief: Structured Notes, 2015; Structured Retail Products, 2015). According to Calvet et al. (2018), a typical retail structured product investor is 58 years old, has an above-average education, and a yearly income of around 48′000 USD.

Issuers have considerable flexibility to tailor structured products (Henderson and Pearson, 2011; Célérier and Vallée, 2017). This flexibility in product design raises the concern that issuers exploit investors by using their privileged access to information. It also weakens the competition mechanism as a potential remedy to this concern. Specifically, issuers can avoid product homogeneity and, hence, impede product comparability, by simply designing products with different terms than those of the competitors.

In this study, we analyze a large database of Swiss structured products provided by Derivative Partners. The database represents an ideal laboratory to explore the role of incomplete information in structured products for several reasons. First, structured products are frequently issued to retail investors (SSPA, Swiss Structured Products Association, 2013). These investors usually have inferior information compared to financial intermediaries (Bhattacharya et al., 2012). Second, the Swiss regulator prescribes the information that structured product issuers must provide to investors in detail (Swiss Bankers Association, 2007). The term sheets that contain this information are highly standardized, which allows us to define proxies of incomplete information. Third, the Swiss market is characterized by standardized product categories, which helps us to collect a large sample of comparable products (Structured Retail Products, 2015). Fourth, the database contains all publicly issued products in Switzerland, which reduces selection bias concerns.

The issuing banks sell the structured products of our database to retail investors. The database does not contain privately placed products that are commonly sold through brokers or independent asset managers. The product launching process typically lasts around two to three weeks (e.g., Egan, 2019). At the beginning of this process, the bank designs the basic product characteristics such as the product type and the underlying. Next, the product enters the subscription period during which investors can submit or cancel buying orders. This period lasts around ten days. At the end of the subscription period, i.e., at the initial fixing date, the bank fixes the final terms of the product such as the issue price, the underlying's reference price, or the barrier level.[2] Investors receive the final

[2]The bank communicates these terms at an indicative level during the subscription period.

term sheet at the initial fixing date, which summarizes the basic product characteristics and the final terms of the product.

Our database contains all product terms and the final term sheet of all structured products on equity underlyings that banks issued on the primary market in Switzerland between January 2005 and December 2010. It comprises 15'170 publicly issued products that target the retail market. Our analysis requires the calculation of the overpricing for each product, which is the difference between the (observable) issue price and a replication price. To prevent that model misspecification or pricing model errors affect our calculation of the replication price, we focus on the products in the database for which we can directly derive this price from the prices of traded market instruments. This criterion leaves us with 1'012 products on single equity underlyings. We exclude products on specific underlying baskets (13'191) in our analysis because there are no traded market instruments on these baskets, which we could use to derive the replication price.[3] We also omit index products (947) because their underlying does not feature the discrete dividend structure that allows us to apply our regression discontinuity design. Finally, we omit 20 products due to missing data. We manually collect the terms of the 1'012 product in our sample from the final term sheets and double-check these terms with the corresponding product terms in the database. In total, we correct 31 entries that contain an error mostly in the "date" item. Our sample of priced products is considerably larger than those used in existing studies. For example, Henderson and Pearson (2011) consider 64 products, Célérier and Vallée (2017) price 141 products, and Arnold et al. (2016) extract 501 products from the same structured products database.[4]

Table 1 reports the number of products in our sample grouped by issuer, product

[3]Deriving the replication price of basket products would require the implementation of a pricing model and the estimation of the underlying baskets' correlation structure.

[4]Vokata (2018) approximates the price of over 20,000 structured products by converting the textual payoff description into a mathematical formula. We cannot use such an approximation in our study because we focus on the relation between product markups and dividends. This relation is sensitive to product details such as the exact final fixing date that are not reflected in the textual payoff description. For instance, just a few days difference in the final fixing date can more than double the markup if this date is just before the ex-dividend date compared to just after the ex-dividend date.

category, and year. The products are issued by two Swiss banks and five international banks in Switzerland. Together, the two Swiss banks, Credit Suisse and UBS, account for more than two-thirds of our sample. Goldman Sachs and Royal Bank of Scotland issue a share of 14.3% and 13.2%, respectively. The sample contains six separate product categories with 87 unique underlyings. Discount Certificates, Barrier Reverse Convertibles, and Bonus Certificates are the most prevalent categories. From 2005–2008, the number of issued products increased annually, while it declined between 2008 and 2010.

INSERT TABLE 1 NEAR HERE

The product categories in our sample have the following profiles:

With a *Discount Certificate*, an investor purchases an underlying stock at a discount but resigns the upside stock performance above a prespecified cap. If the stock closes above this cap at maturity, the investor obtains a payoff equal to the difference between the initial stock and the strike prices. Otherwise, he or she receives the stock performance.

Barrier Discount Certificates likewise embed a discount feature that allows an investor to buy an underlying stock below its market price. The barrier feature provides conditional capital protection. The investor receives a prespecified payoff if the stock never touches the lower barrier during a product's lifetime; otherwise, the capital protection is canceled and the product converts into a Discount Certificate.

Reverse Convertibles have the same payoff profile as Discount Certificates. The only difference is that Reverse Convertibles also pay coupons and have a nominal amount.

Capped Outperformance Certificates allow an investor to participate disproportionately in the performance of the underlying stock above the strike price. If the stock closes below this strike at maturity, the product has the same payoff structure as the stock. Above the strike, the investor obtains a multiple of the difference between the stock and strike prices up to a predetermined cap.

Barrier Reverse Convertibles pay a fixed coupon and are capital-protected if the underlying does not touch a prespecified lower barrier during a product's lifetime; otherwise, the capital protection is canceled and the product converts into a Reverse Convertible.

Bonus Certificates allow an investor to participate in an underlying stock with a down-side protection at a fixed bonus level as long as the stock does not touch a prespecified lower barrier during a product's lifetime; otherwise, the down-side protection is canceled and the Bonus Certificate simply follows the stock performance.

In contrast to a direct investment in an underlying stock, an investor is not entitled to receive the stock's dividend payments. This convention applies to all product categories.

3 Product overpricing and incomplete information

In this section, we first present our main variables, hypotheses, and empirical identification strategy to analyze product overpricing. We then summarize the results for the impact of incomplete information on product overpricing.

3.1 Overpricing measure: Markup

Our dependent variable is the markup ($Markup$). $Markup$ is the percentage difference between a product's issue price and replication price at the initial fixing date:

$$Markup = \frac{Issue\,Price - Replication\,Price}{Issue\,Price}, \tag{1}$$

where $Issue\ Price$ is the initial price at which banks sell a structured product to retail investors. This price includes all issuance fees and commissions that accrue to the investor when he or she buys a product. Using traded instruments of the fixed income and option markets, we derive the *Replication Price* as the market price for institutional investors of a replication portfolio that has the same payout profile as a structured product. Intuitively, a product issuer can hedge its future obligation from issuing a structured product to a retail investor by buying the replicating portfolio at the same time. Thus, the *Replication Price* reflects the market price to the issuer of hedging a structured product and, thus, the issuer's hedging cost.[5] The *Markup* is the percentage difference between the *Issue Price* and the *Replication Price*. Therefore, *Markup* measures the percentage product overpricing at issuance (Henderson and Pearson, 2011). Intuitively, *Markup* can also be interpreted as the %-difference between the prices for retail and institutional investors for the same payout profile at the same time. Issuers determine the *Markup* at the initial fixing date when they fix the final terms of a product.[6]

While product term sheets provide us with issue prices, we also need to calculate the replication prices. To this end, we first determine the fixed-income and option components that replicate a structured product. Second, we derive the price of each component from observed market prices. Finally, the replication price of a structured product is the sum of the prices of the components that replicate its payoff profile. The Appendix illustrates the derivation of replication prices in detail.

As Table 2 shows, the average markup in our sample is 1.48%. This magnitude coincides with the average overpricing in empirical samples of similar simple short-term structured products (Burth et al., 2001; Baule et al., 2008; Célérier and Vallée, 2017). Outside of Switzerland, *Markup*s tend to be higher. Stoimenov and Wilkens (2005) find 3.89% in their German sample and Henderson and Pearson (2011) more than 8% in a US sample.

INSERT TABLE 2 NEAR HERE

[5] We cannot observe the bid-ask spread of the traded instruments in the replicating portfolio. Thus, we follow Henderson and Pearson (2011) and control for proxies of this dimension of the hedging cost in our analysis.

[6] The issue price of some products in our sample is normalized to, for example, 1'000 CHF. Issuers still determine the *Markup* of these normalized products at the initial fixing date by fixing the final product terms. These terms determine the replication price and, hence, the *Markup*.

3.2 Incomplete information: Volatility and dividends

The literature suggests that issuers overprice structured products because they are free to choose contract terms that differ from comparable products (Carlin, 2009; Henderson and Pearson, 2011; Li et al., 2018). Specifically, this product differentiation implies that products are not homogenous, which makes it difficult for investors to compare structured products. Thus, imperfect price competition allows issuers to earn markups in this market.

Our incomplete information hypotheses build on this notion. Specifically, term sheets facilitate the comparability of the inhomogeneous products because they highlight the key differences in the product terms. A better comparability among competing products reduces the issuers' opportunity to exploit investors. The term sheet comparison only imposes relatively limited requirements on investors' financial sophistication. Specifically, the term sheets allow investors to perform a model-free rank ordering of the structured products by comparing the products' key terms even if the investors lack the ability to actually price these products.[7] For example, investors are likely to recognize that a product with a larger coupon is more attractive than a comparable product with a lower coupon without applying a pricing model. Indeed, Egan (2019) argues that a rank ordering is much simpler for structured products than for other financial products such as mutual funds because structured products are completely characterized by a small number of dimensions. Hence, our incomplete information hypothesis relies on the premise that issuers can exploit their volatility and dividend information because that information is not disclosed on the term sheets, which prevents investors from undertaking the model-free rank ordering along these dimensions. Campbell (2006) highlights that many households find solutions to relatively complex investment problems. Thus, it is very plausible that at least some investors can rank order competing products along the

[7]Search costs for investors are relatively small as the term sheets of outstanding products and products in subscription are readily available form the issuers' home page.

dimensions underlying risk or dividend if they have that information.

To investigate whether incomplete information affects overpricing, we first investigate the information content of product term sheets. To this end, we inspect the obligatory information items listed in the Swiss Bankers Association (2007) guidelines. We find that the only two missing items necessary to calculate the products' replication price (that are not publicly available) are the implied volatility of the underlying and expected dividend.[8,9] Next, we manually inspect all term sheets in our database. We find that while each sheet provides all obligatory items, none specifies the implied volatility or the expected dividend. It is very costly for retail investors to obtain information on these missing parameters. One year of access to BLOOMBERG's proprietary system, for example, costs around 25'000 USD per user (Ben-Rephael et al., 2017). Thus, the missing volatility and dividend information causes an information friction that induces incomplete investor information.

Our first hypothesis is that issuers overprice products more when they have a volatility information advantage. For the main analysis, we proxy issuers' volatility information advantage with the simple $Higher\ Vol$ dummy. This dummy is equal to one if the implied volatility ($Impl\ Vol$) of a product's underlying is larger than its historical volatility ($Hist\ Vol$). Following Ben-Rephael et al. (2017), we use the dummy variable in our main analysis because a dummy allows easier interpretation of the differential impact of the volatility information advantage on product overpricing. We also consider the continuous differences between $Impl\ Vol$ and $Hist\ Vol$ as a proxy of issuers' volatility information advantage in Section 6 and obtain similar results.

The intuition behind the $Higher\ Vol$ proxy starts from the observation that the replication prices of all products in our sample decline with the implied volatility of

[8] The implied volatility data for the European underlyings in our sample were not publicly available during our observation period. Today, some of this data is available on public websites such as `finance.yahoo.com`.

[9] Interest rates are not an obligatory information item, but they are publicly available, for example, on the website of the Swiss National Bank (see https://www.snb.ch/en/iabout/stat/statrep). In addition, most term sheets contain an indication of the interest rate.

their underlying. Information on implied volatility is available to issuers through, for example, EUREX or BLOOMBERG. Since such information sources are restricted and very costly, retail investors tend to resort to alternative measures when gauging the expected volatility of a product's underlying. Following the literature, (Daniel et al., 2002; Sirri and Tufano, 1998), they refer to historical information. Our observation that many structured product term sheets contain a picture of the historical price evolution of the product's underlying supports this conjecture.[10] Thus, issuers have an information advantage over retail investors if $Impl\ Vol$ is larger than $Hist\ Vol$. In this case, retail investors underestimate volatility based on their available historical information, and hence overestimate a product's replication price.

Our second hypothesis is that issuers overprice products more when they have a dividend information advantage. We proxy issuers' dividend information advantage with the $Higher\ Div$ dummy. This dummy is equal to one if the dividend forecast ($Forc\ Div$) of a product's underlying is larger than its historical dividend ($Hist\ Div$). Section 6 shows that our results are robust to using the continuous differences between $Forc\ Div$ and $Hist\ Div$ as a proxy of issuers' dividend information advantage

The intuition behind the $Higher\ Div$ proxy is analogous to that of the $Higher\ Vol$ proxy. Specifically, structured product investors are not entitled to receive dividend payments because they solely hold derivative positions on the underlying. Since the replication prices of all products in our sample are positively related to the underlying's stock price, a higher expected dividend payment during the lifetime of a product ceteris paribus reduces the product's current replication price. Product issuers have access to dividend forecasts such as from IBES, which are restricted and costly for retail investors. The latter tend to resort to historical information (Daniel et al., 2002; Sirri and Tufano, 1998). For dividends, historical information is publicly available on the internet.[11] There-

[10]In Figure A1 of the Appendix, we extract a typical picture of the underlying's historical price evolution as provided in a product term sheet from our sample.

[11]For example, on `finance.yahoo.com`.

fore, issuers have an information advantage over retail investors if $Forc\ Div$ is larger than $Hist\ Div$. In this case, retail investors underestimate dividends based on their available information, and hence overestimate a product's replication price.

We now describe the calculation and summary statistics of the volatility and dividend parameters. $Impl\ Vol$ is the annualized implied volatility of an at-the-money put option on a product's underlying with a maturity equal to the product's maturity. We extract this implied volatility at the products' initial fixing date from traded EUREX options as described in the Appendix. $Hist\ Vol$ is the standard deviation of a product underlying's returns over the 255 trading days before the initial fixing date. We choose 255 days because it corresponds to the median product maturity in our sample.[12] Table 2 shows that the average implied and historical volatilities are 28.668% and 31.237%, respectively. For 563 of the 1'012 products in our sample the $Higher\ Vol$ dummy is one.

$Forc\ Div$ is the ratio between the present value of the forecasted dividends during a product's lifetime and the underlying's stock price at the initial fixing date. The dividend forecasts are based on IBES. A forecasted dividend is the average of the analysts' estimates of a stock's next period dividend. $Hist\ Div$ is the ratio between the present value of the historical dividend payments over the 255 days prior to the initial fixing date and the underlying's stock price at the initial fixing date. 94% of the products in our sample are issued on underlyings which pay dividends annually. $Forc\ Div$ and $Hist\ Div$ have similar means and quantiles as shown in Table 2. Both dividend measures have a relatively low standard deviation. For 608 of the 1'012 products in our sample, $Higher\ Div$ is one. The underlyings of 12 products in our sample never pay a dividend and always carry an IBES dividend forecast of zero during our sample period. The $Higher\ Div$ dummy of these products is zero. The correlation between $Higher\ Vol$ and $Higher\ Div$ is 0.08.

[12]Our results are robust to the choice of the number of trading days over which we calculate $Hist\ Vol$ (see Section 6).

3.3 Empirical approach and identification

To investigate the impact of incomplete information on product overpricing, we first run cross-sectional OLS regressions of $Markup$s on our explanatory and control variables. Our regression model is

$$Markup_i = \alpha + \beta_1 Higher\, Dummy_i + \beta_j Controls_{ij} + \epsilon_i, \tag{2}$$

where $Markup_i$ is the $Markup$ of product i. $Higher\, Dummy_i$ represents our information advantage proxy, which is either the $Higher\ Vol$ dummy for volatility or the $Higher\ Div$ dummy for dividends. Hence, $Higher\, Dummy_i$ is our primary explanatory variable.

Our main identification challenge arises from potential omitted variables that are correlated with both $Markup$s and the explanatory variables. We mitigate this challenge by incorporating a comprehensive set of controls, considering price differences as the dependent variable, refining the regressions with interaction effects, and applying a regression discontinuity approach.

First, we incorporate the standard control variables of Henderson and Pearson (2011) in our main analysis, which are captured in the vector of controls $Controls_{ij}$. Specifically, we control for investor attention (*ExcessReturn*, $Market\ Cap$, and *Underlying Turnover*), issuers' hedging costs ($Option\ Volume$), and $Issuance\ Volume$. We calculate $Excess\ Return$ as the 3- and 12-month continuous annual returns of the underlying in excess of the 3- and 12-month continuous annual returns of the Swiss Market Index (SMI), respectively. $Market\ Cap$ is the natural logarithm of the market value of equity of the underlying (in USDbn) at the initial fixing date, and $Turnover$ is the natural logarithm of the dollar value (in USDm) of the cumulative trading volume of the underlying 1- and 3-months prior to the initial fixing date, respectively. $1m\ Call\ Volume$ and $1m\ Put\ Volume$ are the cumulative trading volumes of EUREX call (put) options written on the underlying during the 20 trading days preceding the initial fixing date of a structured product divided by the volume of call (put) options written on all underlyings during the same time period. We calculate $Issuance\ Volume$ as the natural logarithm of a structured product's issuance volume (in USD). As in Henderson and Pearson (2011), we also consider year fixed effects in all regressions to control for aggregate time trends, such as in product demand.[13] In Section 6, we incorporate additional control variables for competition, issuers' default risk, funding needs, the economic environment, a products' time to maturity, product complexity, product category fixed effects, issuer fixed effects, and underlying fixed effects. All data on underlyings, options components, and dividend consensus estimates are from Datastream, the EUREX database, and IBES, respectively. Table 2 presents the summary statistics of all controls.

Second, the idea behind using price differences ($Markup$s) as the dependent variable is that the law of one price should hold in perfect markets. Thus, analyzing $Markup$s allows us to focus on the market frictions that drive a wedge between the prices to retail and institutional investors for the same payout profiles. In other words, using $Markup$s mitigates the concern that our explanatory variables simply capture omitted product price determinants (that are not associated with market frictions) because the impact of such determinants should cancel out in the price differential.

Third, we confirm our information hypothesis by showing that the relation between the dependent and explanatory variables is stronger when the information channel is more plausible. To this end, we interact our explanatory variables with several additional variables, which we include in Table 2. $Delta$ ($Vega$) is a product value's first-order derivative with respect to the price (volatility) of the underlying, in which the product value is the replication price. We calculate these derivatives by using the Black-Scholes formula. For products with barrier options, we estimate $Delta$ and $Vega$ numerically. We scale each $Delta$ and $Vega$ by the product's initial value to obtain each product's %

[13]Our results are robust to considering year-month fixed effects (not tabulated).

value-sensitivity.[14] The *Delta* of each product in our sample is positive, which implies that product values rise if the underlying price increases (or the dividend expected over a product's lifetime declines). The mean *Delta* of 1.56 in Table 2 implies that, on average, initial product values increase by 1.56% if the underlying increases by 1%. The *Vega* of each product in our sample is negative, which suggests that product values decline if the underlying's volatility increases.[15] The mean *Vega* of −0.46 in Table 2 implies that, on average, initial product values decline by 0.46% if the underlying's volatility increases by one percentage point.

We also consider *IVolatility*, which is a dummy variable equal to one if a product's underlying is covered on IVolatility.com at the initial fixing date and zero otherwise. IVolatility.com is a widely used volatility information provider.[16] It is the first provider to offer single volatility quotes on selected individual stocks to retail investors. Alternative providers only sold entire volatility information packages during our sample period. The single quote feature is important for our study because the coverage of an underlying on IVolatility.com considerably reduces the issuers' volatility information advantage over retail investors for that underlying. Specifically, a structured product investor could acquire the volatility information of a product with a single quote-covered underlying for a few dollars but would have to buy the entire volatility package for several thousand dollars if he or she wanted the volatility information of an uncovered stock.[17] For 768 products in our sample, volatility information on the underlying was available on IVolatility.com at the initial fixing date. We also include *IBES Uncertainty* as a measure of dividend forecast uncertainty. *IBES Uncertainty* is the standard deviation of analysts' IBES dividend forecasts for an underlying on the initial fixing date. In addition, we collect

[14] We have different product categories in our sample with a large variation of the initial value. Thus, we need to scale the (absolute) *Delta* and *Vega* to compare these sensitivities across products and product categories.

[15] The primary reason for the negative *Vega* is that the products are capped. Thus, a higher volatility increases a product's downside potential without equivalently increasing the upside potential.

[16] See `www.ivolatility.com`.

[17] The price of single quotes on IVolatility.com starts at 3 USD.

structured products' trading size as a proxy of investors' information access because the literature suggests that the information sets used by investors initiating small trades are systematically inferior to those used by investors initiating large trades (Easley and O'Hara, 1987; Bhattacharya, 2001; Battalio and Mendenhall, 2005; Bhattacharya et al., 2007). We calculate $Trading\ Size$ as the logarithm of the average trading size of each structured product in USD on the secondary market.

Finally, we establish a causal link between issuers' information advantage and product overpricing by applying a regression discontinuity approach in Section 4.

3.4 Overpricing and incomplete volatility information

We start by investigating the impact of incomplete volatility information on $Markup$s. In Column (1) of Table 3, we first replicate the regression of Henderson and Pearson (2011) to ensure that our setting is consistent with their study. As in Henderson and Pearson (2011), $Impl\ Vol$ is significantly positively associated with $Markup$s and the remaining controls are mostly insignificant or not robust (see Columns (1)–(5)). The only difference is that the coefficient of $Issuance\ Volume$ is significantly negative in our setting, while it is insignificant in Henderson and Pearson (2011). This negative sign suggests a negative relation between issuance volume and overpricing.

INSERT TABLE 3 NEAR HERE

Next, we test our hypothesis by adding the $Higher\ Vol$ dummy in Column (2). The coefficient of $Higher\ Vol$ implies that issuers demand a 1.006% larger $Markup$ for products with a higher implied than historical volatility. This magnitude is important, accounting for more than two-thirds of the average $Markup$s. The result suggests that issuers overprice products when they have a volatility information advantage; that is, when retail investors underestimate volatility based on their historical information.

The alternative financial literacy hypothesis suggests that issuers install larger $Markup$s for products with higher $Impl\ Vol$ because retail investors are unaware of the negative impact of volatility on structured products' replication prices (Henderson and Pearson, 2011). We address the concern that *Higher Vol* could simply identify a (potentially non-linear) dimension of *Impl Vol*, and hence the financial literacy hypothesis, in two ways. First, we show in Section 6 that the coefficient on *Higher Vol* is robust to using *Impl Vol Squared* as an additional control. Second, we calculate the average *Impl Vol* of products with a *Higher Vol* dummy of one. Their average *Impl Vol* (26.527%) is, in fact, significantly smaller than that of products with a *Higher Vol* dummy of zero (31.353%), with a t-statistics of 6.93 using a two-sample t-test. Thus, products with a *Higher Vol* dummy of one carry a larger markup that cannot be explained by a higher implied volatility and, hence, the financial literacy hypothesis.

We also investigate whether the quantitative magnitude of the *Higher Vol* coefficient is consistent with our information exploitation hypothesis. To this end, we first approximate the average "value" to issuers of their information advantage with *Higher Vol* products and then compare this value to the size of the coefficient. Information exploitation implies that the *Higher Vol* coefficient should be an economically significant portion of the value of issuers' information advantage but still lie below 100% of this value. Otherwise, alternative explanations must drive the coefficient. To approximate the value of issuers' information advantage, we compute the difference between the implied and historical volatilities of each product with a *Higher Vol* dummy equal to one and multiply each difference with the product's absolute vega. Intuitively, the resulting values are an investor's percentage product misvaluation if he or she would rely on historical rather than implied volatility. The average of these values is 1.900%. Thus, the coefficient of *Higher Vol* in Column (2) suggests that issuers are, on average, able to exploit approximately 53% (1.006% of 1.900%) of their information advantage,[18] which is in the plausible range.

We now present several refinements to support our first hypothesis that issuers exploit

[18]This comparison assumes that products with a *Higher Vol* dummy equal to zero neither carry an information advantage nor an information disadvantage.

incomplete volatility information.

The coefficient on the interaction $Higher\ Vol$ x $Vega$ in Column (3) shows that the impact of $Higher\ Vol$ on $Markup$s is stronger if $Vega$ is more negative. This result is consistent with the information exploitation hypothesis. Specifically, a product with a more negative $Vega$ is particularly sensitive to volatility information. Hence, an investor overvalues this product more if he or she underestimates its volatility by a given amount, which offers issuers a better opportunity to exploit the information advantage channel.

In Column (4), we investigate how the coverage of a product's underlying at the initial fixing date on IVolatility.com affects our results. The negative and significant coefficient of the interaction term between $Higher\ Vol$ and $IVolatility$ implies that, consistent with our hypothesis, improving retail investors' access to volatility information mitigates issuers' exploitation of this information channel.[19] We argue that improved information access sharpens investors' ability to compare competing products along the volatility dimension, and thus reduces issuers' tendency to overprice securities for which they have a volatility information advantage. This channel could operate even if investors do not actually access $IVolatility$. Specifically, the pure possibility that investors could easily collect (and compare) implied volatilities may induce issuers to cease exploiting volatility due to reputation concerns.

Finally, the interaction between $Higher\ Vol$ and $Trading\ Size$ as a proxy for investors' information access has a significantly negative coefficient, as Column (5) shows. This result also supports our incomplete information exploitation hypothesis because it implies that issuers use their information advantage particularly to overprice securities when selling products to investors with inferior information access.

[19] If we include underlying fixed effects, the coefficient of the interaction term is -0.54 and statistically significant at the 10% level. Thus, the underlying specific characteristics do not drive this effect, but rather the change in the availability of implied volatility information does.

3.5 Overpricing and incomplete dividend information

We now test whether product issuers exploit their information advantage regarding dividends. We present the results in Table 4. In the first column, we include *Forc Div* as a measure of forecasted dividend payments. The significantly positive coefficient of *Forc Div* shows that an increase in the forecasted dividend yield raises the *Markup*. The magnitude of the coefficient implies that increasing *Forc Div* by one standard deviation (2.18) enhances the *Markup* by 0.15%.

INSERT TABLE 4 NEAR HERE

To determine whether incomplete information plays a role or whether this result is simply driven by a financial literacy argument; that is, by the fact that retail investors do not understand that product replication prices decline with dividends, we incorporate our proxy for issuers' information advantage on dividends in Column (2). Products with *Higher Div* equal to one carry an *Markup* that is 0.768% higher than for products with *Higher Div* equal to zero on average. This effect is economically important because it corresponds to an increase of more than 52% of the average *Markup*. This result provides a first confirmation of our second hypothesis that issuers collect higher *Markup*s when they have a dividend information advantage over retail investors.

To investigate whether the quantitative magnitude of the *Higher Div* coefficient is consistent with our information exploitation story, we first approximate the average "value" to issuers from their information advantage with *Higher Div* products and then compare this value to the size of the coefficient. Information exploitation implies that the *Higher Div* coefficient should be an economically significant portion of the value of issuers' information advantage but still lie below 100% of this value. Otherwise, alternative explanations would drive the size of the coefficient. To approximate the value of issuers' information advantage, we compute the difference between the present values of forecasted IBES dividends and historical dividends over the lifetime of each product with a *Higher Div* dummy equal to one and multiply each difference with the product's absolute delta. Intuitively, this value is an investor's percentage product overvaluation if he or she would rely on historical instead of forecasted dividends. The average of this value is 1.497%. Thus, the coefficient of *Higher Div* in Column (2) suggests that issuers are, on average, able to exploit around 51% (0.768% of 1.497%) of their information advantage,[20] which is in the plausible range.

In Column (3), we include the interaction between *Higher Div* and *Delta*. If *Delta* is larger, underestimating dividends has a stronger impact on retail investors' perceived replication price. The significantly positive coefficient of this interaction suggests a stronger dividend information exploitation for products with a higher sensitivity to dividend information. This finding supports our dividend information exploitation story.

As Column (4) shows, the interaction between *Higher Div* and *IBES Uncertainty* has a significantly negative coefficient. This result is consistent with the information exploitation hypothesis because it implies that issuers exploit their privileged access to information particularly when their information source is more accurate.

Column (5) shows that the interaction between *Higher Div* and *Trading Size* has a significantly negative coefficient. This result implies that issuers exploit their dividend information advantage to overprice securities particularly when selling products to investors with inferior information access, which confirms the information exploitation hypothesis.

Overall, Section 3 suggests that volatility and dividends cause two key investor information frictions that affect issuers' product pricing decision. The literature describes additional alternative motives for issuers to overprice and issue structured products (see, e.g., Henderson and Pearson, 2011; Célérier and Vallée, 2017; Li et al., 2018). Thus, we neither assert that information frictions entirely explain issuers' overpricing decision nor controvert that issuers launch products without an information advantage due to alternative motives. We simply highlight that investor information frictions are one important

[20] This comparison assumes that products with a *Higher Div* dummy equal to zero carry neither an information advantage nor an information disadvantage.

factor that explains a substantial part of the level and cross-sectional variation of the products' overpricing.

4 A regression discontinuity design for information exploitation

We now investigate the hypothesis that issuers exploit their dividend information advantage in a regression discontinuity design (RDD) to provide an estimate of a clean causal effect of information frictions on overpricing. To this end, we exploit the impact of a shock to issuers' dividend information advantage on product overpricing. Public dividend announcements are a perfect candidate for such a shock in this analysis for two reasons. First, they publicly inform investors about the upcoming dividend payment, and hence represent a negative shock to issuers' dividend information advantage. Second, it is unlikely that investors experience a shock to their financial sophistication level at dividend announcement dates, which helps us to differentiate the information exploitation hypothesis from the investor sophistication hypothesis.

4.1 RD approach and results

The main idea behind our RDD is that if issuers' dividend information advantage causes overpricing, then this overpricing should experience a negative shock at dividend announcement dates. Thus, we test whether products with a dividend information advantage for issuers; that is., products with $Higher\ Div = 1$, exhibit a discontinuity of $Markup$s at dividend announcements. To this end, we follow the standard parametric regression discontinuity (RD) approach in Lee and Lemieux (2010). We test alternative RD methodologies and specifications in Section 6.

We first define our assignment variable as the difference between the closest dividend announcement date and the product's initial fixing date expressed in days. The closest dividend announcement date is the product underlying's dividend announcement date closest to the product's initial fixing date. We collect data on dividend announcement dates from Datastream. An assignment variable greater or equal to zero (treated) implies that the dividend is announced after or at the initial fixing date.[21] Treated products exhibit a dividend information advantage for the issuer because the issuer has access to IBES dividend forecasts. A negative value of the assignment variable (non-treated) implies that the dividend is announced before the initial fixing date. Non-treated products exhibit a smaller dividend information advantage than treated products do because the next dividend was publicly announced just before the product is launched.

The outcome variable is $Markup$, which is our measure of overpricing. Figure 1 depicts the $Markup$s of all products with a dividend information advantage ($Higher\ Div$ =1) around the assignment variable of zero (threshold). We fit a linear function on either side of the threshold using binwidths of 3 days. Each bin represents the average $Markup$ over 3 days. The jump in $Markup$s at the threshold suggests that product overpricing experiences a negative shock at dividend announcement dates and, thus, a causality between issuers' dividend information advantage and overpricing.

INSERT FIGURE 1 NEAR HERE

If the variation in the treatment near the threshold is approximately randomized, then the treated and non-treated products should differ only with respect to issuers' information advantage. To ensure this randomization condition, issuers should not be able to completely manipulate the difference between dividend announcement and initial fixing dates (McCrary, 2008). We provide statistical and intuitive practical evidence that our setting satisfies the no-complete manipulation condition. First, we test this condition with the standard manipulation test following McCrary (2008) and find no discontinuity in the density function of the assignment variable at the threshold (t-statistics of -0.48).

[21] We do not define the assignment variable on an intraday level because our sample features no observation for which the initial fixing date corresponds to the dividend announcement date exactly.

Second, product issuers must plan, structure, market, subscribe, and launch a new product before the initial fixing date, which takes several weeks. As dividend announcement dates vary considerably, issuers would have to stop initiating new products on most underlyings several weeks or months before the dividend announcement period between March and April to avoid negative values of the assignment variable.[22] The opportunity cost of such a manipulation in terms of the foregone $Markup$s from issuing products would certainly be very large.

We now establish the RDD to test how issuers' information advantage affects the degree of product overpricing. Since we expect no functional relationship between our assignment variable and the outcome variable, we use a local polynomial of order one to construct the point estimator in our main analysis. We also present the results when using a local polynomial of order two.[23] The regression model is

$$Markup_i = \alpha_1 + \beta_1 Days_i + After_i[\alpha_2 + \beta_2 Days_i] + \epsilon_i, \tag{3}$$

where $Markup_i$ is the outcome variable, $Days_i$ is the difference between the dividend announcement date nearest to the initial fixing date and the initial fixing date measured in days, and $After_i$ is a dummy equal to one if the dividend announcement date nearest to the initial fixing date occurs on or after the initial fixing date and zero otherwise. α_2 is the coefficient of discontinuity at the threshold. If issuers overprice products more when they have a higher information advantage, α_2 should be positive. Following Lee and Lemieux (2010), we use heteroskedasticity-robust standard errors.

The RDD requires that we specify a bandwidth determining the number of observations on either side of the threshold. We use mean square error-optimized bandwidths based on the methodology of Calonico et al. (2014). The optimal bandwidths of the

[22]For instance, the standard deviation of the year-on-year differences between a company's subsequent dividend announcement dates in our sample is more than 30 days.

[23]As Gelman and Imbens (2018) suggests, we abstain from using third or higher-degree polynomials.

$Markup$s require 79 observations on the left-hand side and 119 observations on the right-hand side of the threshold. These bandwidths correspond to a time window of [-57, 57] days around the initial fixing date.

Column (1) of Table 5 presents the results of Regression (3). We find a positive and significant discontinuity in $Markup$s of 1.495% with a t-statistic of 3.14 at the threshold. The upward jump in $Markup$s implies that issuers overprice products more when they have a larger information advantage over investors. The magnitude of this discontinuity is economically important. Specifically, the average $Markup$ of the products in our RDD subsample is 1.70%; thus, the $Markup$ increases by 88% of the average $Markup$ at the threshold. Column (2) of Table 5 shows that the discontinuity is also significant but smaller in magnitude when we include a local polynomial of order two in Regression (3).

INSERT TABLE 5 NEAR HERE

To further verify the RDD assumption of local randomization, we also investigate whether control variables exhibit discontinuities around the threshold.[24] To this end, we follow Lee and Lemieux (2010) by applying a Seemingly Unrelated Regression (SUR) based on a system of equations similar to Eqn. (3) for the standard control variables of Section 3.[25] We perform a χ^2 test to determine whether the respective discontinuity coefficients α_2 of all equations are jointly equal to zero. A rejection of this null hypothesis could imply that the treated products we use in our RDD approach discontinuously differ from the non-treated products along dimensions other than the information advantage, which could challenge our main conjecture. We find, however, that our data are consistent with no discontinuities for any of the control variables (p-value = 0.28).

Table 6 presents several refinements of the basic RDD approach to confirm our conjecture that issuers' information advantage causes overpricing and rule out alternative

[24]Note that shocks to public observable product price determinants that are not associated with market frictions, such as the stock price or LIBOR, should not affect $Markup$ because $Markup$ is the %-difference between the issue prices and the replication price.

[25]Specifically, we use $Impl\ Vol$, $Forc\ Div$, $Market\ Cap$, $3m\ Excess\ Return$, $12m\ Excess\ Return$, $1m\ Turnover$, $3m\ Turnover$, $1m\ Call\ Option\ Volume$, $1m\ Put\ Option\ Volume$, and $Issuance\ Volume$.

explanations. For each refinement, we recalculate the mean square error-optimized bandwidths following Calonico et al. (2014).

INSERT TABLE 6 NEAR HERE

A first alternative explanation is that dividend announcements reduce hedging costs, and hence $Markup$s, because they mitigate issuers' uncertainty about future dividends. Thus, we repeat the RDD analysis for the subsample of products that do not exhibit an information advantage for the issuer ($HigherDiv = 0$). If issuers' dividend uncertainty causes the decline in $Markup$s at the threshold, the discontinuity should also be present in this subsample. Column (1) of Table 6 shows that this discontinuity is not significant, suggesting that issuers' dividend uncertainty does not drive our results.

Second, firms typically announce earnings and dividends on the same date. Dividends are a replication price determinant of structured products beyond the publicly observable stock price because a relevant determinant of this price is the publicly observable stock price net of the present value of the expected dividends. In contrast, earnings are not a replication price determinant beyond the publicly observable stock price because the stock price already reflects the market consensus on earnings. Hence, the replication price formulas 5 to 10 in the Appendix contain a dividend component but not an earnings component. As a consequence, earnings are not a plausible source of issuers' information advantage over retail investors to price structured products. Besides this intuitive argument, we provide additionally statistical evidence that earnings information does not drive our dividend information results. To this end, we repeat our analysis with the subsample of products, for which the dividend announcement date does not coincide with the earnings announcement date. Column (2) shows that the discontinuity at dividend announcements is also significant in this subsample.

Third, a potential caveat of our approach is that IBES data are only updated monthly.[26] Thus, some products may carry an IBES dividend estimation at the initial fixing date

[26]Historical IBES files are updated on each Thursday before the third Friday of every month.

that was not yet updated after the last dividend announcement date. We repeat our baseline analysis by omitting the products for which the IBES data were not updated between the dividend announcement date and the initial fixing date. Column (3) shows that our results hold in this case.

Fourth, dividend announcements could attract retail or institutional investors' attention. Hence, attention spikes on dividend announcement dates may cause the discontinuity in $Markup$s. To derive a proxy of attention for specific trading days, we follow Barber and Odean (2007) by defining $Abnormal\ Trading\ Volume$ as the ratio between a stock's trading volume on a certain trading day and the average daily trading volume over the previous 252 trading days. In Column (4) of Table 6, we repeat our main RDD analysis in subsamples as in Chemmanur and Tian (2018). Specifically, we split our sample at the sample median of $Abnormal\ Trading\ Volume$ and test the discontinuities of the $Markup$s in the two subsamples. The results in Column (4) suggest that high attention on a stock upon its dividend announcement is not the driving force behind the discontinuity of $Markup$s at dividend announcement dates because the discontinuities are significant in both subsamples. In addition, the magnitude of the discontinuity coefficient is larger in the subsample with low $Abnormal\ Trading\ Volume$.

A final concern is that our calculation of $Markup$s, which uses dividend estimates to derive the replication price, causes the discontinuity in the outcome variable around the threshold. To address this model misspecification or pricing model error concern, we repeat the RDD approach with an alternative measure of overpricing that is independent of our replication price calculation. Specifically, we use unexplained product performance (UP), which is the fraction of a product's ex-post performance that is not explained by the evolution of its underlying, as a measure of overpricing. The idea behind this measure is that higher initial overpricing reduces investors' ex-post performance from the products (Henderson and Pearson, 2011). To obtain the outcome variable UP, we collect the residuals of the regression

$$
\begin{aligned}
&Product\,Performance_i = \alpha + \beta_1 Return\,Underlying_i + \\
&\beta_2 Product\,Category_i + \beta_3 Return\,Underlying_i\,x\,Product\,Category_i + \\
&\beta_4 Return\,Underlying_i^2 + \beta_5 Return\,Underlying_i^2\,x\,Product\,Category_i + \epsilon_i,
\end{aligned}
\tag{4}
$$

where *Product Performance* is the annualized ex-post performance of product i calculated as the return between the issue price and the final payoff, and *Return Underlying* is the annualized ex-post total return of the underlying of product i multiplied by *Delta*. Multiplying the underlying return by *Delta* accounts for a structured product's sensitivity to the underlying. Since alternative product categories exhibit diverse payout profiles, we also incorporate *Category*, which captures the product category of product i, and its interaction with *Return Underlying*. Because structured products entail derivative components, their return is not linearly related to the underlying. Therefore, we also include the quadratic term of *Return Underlying* and its interaction with *Product Category*. We present the regression output in Table 7. With an R-squared of 94%, the regression model reflects the variation in *Product Performance* very well. The residuals of Eqn. (4) have a standard deviation of 0.08. We use these residuals as our outcome variable *UP*.[27] A low *UP* indicates high initial overpricing.

INSERT TABLE 7 NEAR HERE

We present the results using *UP* as the outcome variable in our RDD in Table 8. As expected, we find a significantly negative discontinuity in *UP* of -0.03 at the threshold between treated and non-treated products. Column (2) shows that the discontinuity is also significant for a local polynomial of order two.

INSERT TABLE 8 NEAR HERE

Overall, our RDD approach confirms the conjecture of Section 3.2 that issuers over-

[27] Our results are robust to many alternative specifications of Eqn. (4), such as omitting the squared terms of the underlying return.

price products more when their information advantage is larger. Importantly, the results of the RD approach allow us to distinguish our hypothesis from alternative hypotheses. For example, it is unlikely that investors' sophistication level features a discontinuous jump at the dividend announcement date.

5 Product design and incomplete information

Issuers have considerable flexibility to tailor structured products (Henderson and Pearson, 2011; Célérier and Vallée, 2017), which allows us to investigate the impact of their information advantage on product design. To this end, we employ a simple matched-sample approach to compare the information advantage of the underlyings that issuers choose for a product with otherwise similar underlyings that they do not choose. The goal of this matching approach is to control for cross-underlying variation in characteristics that may affect issuers' tendency to select a certain underlying (Roberts and Whited, 2013).

We proceed as follows. We start by defining the set of underlyings that issuers might choose for their structured products. We assume that this available set consists of all underlyings that have ever been chosen by any issuer during our observation period. For each week and underlying in the available set, we calculate $Impl\ Vol$, $Hist\ Vol$, $Forc\ Div$, and $Hist\ Div$ for a time to maturity of 255 days because this time span corresponds to the median product maturity in our sample. We proxy issuers' information advantage with our $Higher\ Vol$ and $Higher\ Div$ dummies defined in Section 3.2.

For each underlying that issuers actually choose for a structured product, we then select the five closest neighbors of this chosen underlying in the initial fixing week with respect to the square root of the sum of the squared distances weighted by the inverse sample covariance (the Mahalanobis distance) from the available set.[28] As matching variables, we apply the underlying specific control variables from Section 3. In addition,

[28] The results are similar if we use, for example, the three or four closest neighbors (not tabulated).

we impose that these matched underlyings are listed in the same index as the chosen underlying and belong to the same industry based on the two-digit Standard Industrial Classification (SIC) code. The underlyings of 579 products in our sample belong to the Swiss Market Index (SMI) and those of 292 products are listed in the EuroStoxx 50 Index. We assign the remaining 141 product underlyings to the category "Other". We lag the matching variables by up to three weeks because issuers need to determine the basic product characteristics such as the underlying before the initial fixing date, i.e., at the time they initiate a product launch process (see Section 2).

Next, we calculate the portion of the chosen underlyings and the matched underlyings for which the $Higher\ Vol$ dummy is equal to one, i.e., for which the implied volatility is larger than the historical volatility. We first lag the matching variables by three weeks. Column (1) of Panel A in Table 9 shows that whereas 61.5% of the chosen underlyings have an implied volatility that is larger than the historical volatility, only 56.9% of the matched underlyings carry this volatility information advantage for the issuer. Using the one-sided t-test, we find that this difference is statistically significant. Economically, chosen underlyings are, on average, 8.1% ((61.5-56.9)/56.9) more likely to carry a volatility information advantage than matched underlyings. We also calculate the portion of the chosen underlyings and the matched underlyings for which the $Higher\ Div$ dummy is equal to one. We find that 70.3% of the chosen underlyings and 64.4% of the matched underlyings carry a dividend information advantage for the issuer. Again, this difference is highly statistically and economically significant. Specifically, chosen underlyings are, on average, 9.2% ((70.3-64.4)/64.4) more likely to carry a dividend information advantage for the issuer than matched underlyings. Columns (2) and (3) show that the results are similar if we lag the matching variables by two or one week. Only $Mean\ Difference$ $Higher\ Vol$ in Column (3) is borderline insignificant.

INSERT TABLE 9 NEAR HERE

Overall, our product design analysis implies that one important reason for issuers to select a certain underlying for a new structured product is to create an information advantage over retail investors.

In Panel B of Table 9, we also calculate the average value of *Impl Vol* and *Forc Div* for both chosen underlyings and matched underlyings. The financial literacy hypothesis would imply that because retail investors are unaware of the negative impact of volatility and dividends on structured products' replication prices, issuers would tend to select underlyings with higher *Impl Vol* and *Forc Div* to boost *Markup*s. Except for *Mean Difference Forc Div* in Column (3), however, none of the differences is significantly above zero. Thus, our result in Panel A of Table 9, that issuers select underlyings for which they have a stronger information advantage, cannot be explained by the alternative financial literacy hypothesis.[29]

6 Robustness

We conduct several robustness tests for our overpricing and regression discontinuity results, which we summarize in this section.

6.1 Robustness of overpricing results

In Tables 10 and 11, we report on alternative specifications of the main regressions presented in Tables 3 and 4. We include *Impl Vol*, *Higher Vol*, *Forc Div*, and *Higher Div* in all regression specifications.

INSERT TABLE 10 NEAR HERE

INSERT TABLE 11 NEAR HERE

To incorporate a potential non-linear relationship between volatility or dividend and *Markup*, we consider the square product of *Impl Vol* (*Impl Vol Squared*) and *Forc*

[29]As an alternative test, we repeat the matching procedure by including *Impl Vol* and *Forc Div* as matching variables. The chosen underlyings are still significantly more likely to have *Higher Vol* and *Higher Div* dummies equal to one than the matched underlyings (not tabulated).

Div (*Forc Div Squared*) in our regression model. Columns (1) of Tables 10 and 11 show that the results for *Higher Vol* and *Higher Div* are robust to this specification.

A systematic error in the calculation of *Impl Vol* could introduce a correlation between our independent variable *Markup* and the control variables *Impl Vol* or *Higher Vol* because some structured products entail options (used to calculate the *Markup* via the replication price) with maturity and strike that are close to those of the control variable *Impl Vol*. We address this endogeneity concern with the approach suggested in Henderson and Pearson (2011). Specifically, we use the implied volatility of at-the-money put options with a time to maturity of 182 days to define *Impl Vol* 182 and *Higher Vol* 182. We then exclude all products with a maturity below 200 days in the regression, such that no product has a maturity close to 182. Column (2) of Table 10 shows that the *Higher Vol* 182 coefficient is still significantly positive.

We also show that our results are robust to the specification of the number of trading days over which we calculate the historical volatility of a product underlying's return. Specifically, we replace *Higher Vol* with *Higher Vol* 162 in Column (3) of Table 10. The only difference in this specification is that we calculate the historical volatility used in *Higher Vol* 162 over half a year (162 trading days) instead of 255 trading days prior to the initial fixing date. Thus, *Higher Vol* 162 is a binary variable that is equal to one if *Impl Vol* is larger than the historical standard deviation of a product underlying's returns over the previous 162 trading days and zero otherwise. The coefficient of *Higher Vol* 162 is still positive and significant. In addition, we test a battery of alternative time span specifications for the calculation of the historical volatility. For example, we calculate the historical volatility over the same number of trading days as a product's time to maturity (not tabulated). Our results are robust to these alternative definitions.

In Column (4) of Table 10 and Column (2) of Table 11, we replace our explanatory dummies with continuous variables. *Vol Difference* is the difference between *Impl Vol* and *Hist Vol*. *Div Difference* is the difference between *Forc Div* and *Hist Div*. The coefficients of both variables are positive and significant. Thus, a larger volatility or dividend information advantage entails a higher $Markup$.

Another concern with our results is a potential correlation of unobserved heterogeneity at the product category level with at least one of the main explanatory variables. For example, issuers may install higher $Markup$s for certain product categories. The same problem arises if certain issuers require higher $Markup$s than others do. Thus, we rerun the regressions with product category and issuer fixed effects. Our results are robust to this alternative specification, as Column (5) of Table 10 and Column (3) of Table 11 show.

In addition, cross-sectional heterogeneity of underlyings or correlated standard errors within underlying clusters could affect the coefficients of the information advantage proxies. To address this concern, we include underlying fixed effects and clustered standard errors at the underlying level in Column (6) of Table 10 and Column (4) of Table 11. Our results are robust to this specification.

Next, we include a battery of additional control variables that could affect our results in Column (5) of Table 10. We incorporate $Hist\ Vol$ and $Hist\ Div$ to account for the concern that historical information could drive the results for our information advantage proxies $Higher\ Vol$ and $Higher\ Div$, respectively.

The degree of competition in the structured products market may also affect issuers' $Markup$ decision. Thus, we incorporate the Herfindal-Hirshman-Index ($HH - Index$) as an additional control, which we calculate based on issuers' market share of currently active products at each date. A higher $HH - Index$ indicates a more monopolistic market.[30]

Structured products may also serve banks as a medium-term funding source. Thus, issuers' funding needs can influence product pricing. As in Affinito and Tagliaferri (2010), we control for $Funding\ Needs$ with issuers' quarterly ratio of deposits to total assets.

[30]We also use the number of active products and banks as alternative proxies for competition. The results are robust to these alternatives.

Investors face the issuer's default risk when buying a structured product, which could affect $Markup$s (Baule et al., 2008). Thus, we incorporate the issuer's $CDS\ Spread$ as a proxy for default risk. We interpolate this spread to each product's maturity.

The economic environment influences the market conditions under which structured products are issued. We include the Economic Barometer published by the KOF Swiss Economic Institute as a proxy for the economic environment. The Economic Barometer is based on the month-to-month growth rate of Switzerland's GDP and aims to measure the Swiss business cycle. This proxy (together with the year fixed effects and the $CDS\ Spread$) also controls for potential financial crisis effects on overpricing.

We also control for a product's $Time\ to\ Maturity$. In addition, we include a dummy variable that is equal to one if a product has a time to maturity of one year or shorter to control for the tax advantage of these products in Switzerland ($Short-term\ Product$).[31]

Following the notion of Célérier and Vallée (2017) that complexity increases $Markup$s, we also incorporate a proxy for complexity. As in Célérier and Vallée (2017), we define complexity by the number of features contained in a product's payoff formula ($Features$).

Another potential concern with our volatility result is that a volatility risk premium in the spirit of e.g., Carr and Wu (2016) affects our conjecture. We address this issue in two ways. First, whereas the volatility risk premium may affect option prices, the advantage of using $Markup$s in our regressions is that the $Markup$ corresponds to the difference in prices between retail and institutional investors of the same payout profile. Thus, without market frictions, the volatility risk premium should affect the prices of the same payout profile for different investors to the same extent and, therefore, not drive the price differential. Second, we include $VSMI$. $VSMI$ is an index based on the implied volatilities of SMI options across maturities, which is a standard proxy for market uncertainty (Ang et al., 2006).

The result that our information advantage proxies $Higher\ Vol$ and $Higher\ Div$ play a

[31] Structured products taxation is regulated in the circular letter issued by the Federal Tax Administration on April 12, 1999 (not available in English).

significant role in explaining *Markups* is robust to these additional controls (see Column (5) of Table 11). In addition, the coefficient of *Hist Vol* is significantly negative, indicating that issuers reduce *Markup* when an underlying recently exhibits a high volatility.[32] The significantly positive coefficient of *Funding Needs* suggests that products of issuers with higher *Funding Needs* exhibit larger *Markups*. We also find a significantly positive relation between the economic environment and *Markups*. As expected, products with a longer *Time to Maturity* have larger *Markups*. The significantly positive coefficient of *Features* confirms the relationship between complexity and *Markups* in Célérier and Vallée (2017).[33] *VSMI* is significantly negative, suggesting that higher market uncertainty reduces *Markups*. The remaining control variables are insignificant.

6.2 Robustness of regression discontinuity approach

Our RDD results are robust to alternative methodologies and specifications.

Following Imbens and Lemieux (2008), we investigate the sensitivity of our results to the bandwidth choice. We find that the discontinuity is robust to alternative bandwidths. For example, the discontinuity coefficient is still significant if we double the bandwidth (coefficient of 0.83% and t-statistic of 1.90).[34] Our results are also robust to alternative bandwidth selection procedures, such as the coverage error-rate optimization.

In addition, we implement a nonparametric RDD based on bias-corrected RDD estimators and robust standard errors as suggested by Calonico et al. (2014). In this approach, we use a triangular kernel function to construct the local-polynomial estimator. Our results are robust to this methodology (not reported).

[32] If we include *Hist Vol* as a control variable, the model exhibits considerable multicolinearity measured by the Variance Inflation Factor. The coefficient of *Higher Vol* remains significantly positive if we exclude *Hist Vol* from the model in Column (5).

[33] We test alternative complexity measures and obtain similar results (not tabulated).

[34] As expected, the magnitude and significance of the coefficient decline for very large or very small bandwidths. For very large bandwidths, the observations far away from the threshold diminish the coefficient. For very small bandwidths, the low number of observations reduces the coefficient's significance.

7 Conclusion

We analyze a large database of structured product term sheets and find that issuers do not disclose information about the volatility and dividend of the products' underlyings. We then show that products with a volatility information advantage for issuers exhibit a 68% higher overpricing than without this advantage, and products with a dividend information advantage for issuers exhibit a 52% higher overpricing. Thus, information frictions have important explanatory power for the existence and cross-sectional variation of overpricing in the financial innovation market. We present a battery of tests including a standard RDD setting to establish the hypothesis that issuers exploit their information advantage. We also show that banks design products toward the information friction sources that we identify. This result suggests that financial innovators not only exploit existing information frictions, but even create such frictions in the financial system, which is a concern for financial stability (e.g., Gennaioli et al., 2012).

There is a vigorous ongoing debate on the caveats of financial innovation, such as product complexity, investor sophistication, and behavioral biases (e.g., Carlin, 2009; Zingales, 2015; Célérier and Vallée, 2017; Li et al., 2018). Our study adds to this debate along two dimensions. First, we show that investor information frictions are an additional important caveat, which appears to have largely escaped regulators in charge of investor protection and market stability. The Dodd-Frank Act, for instance, only broadly suggests that issuers should disclose adequate information to investors. Second, the identification of volatility and dividends as the information types causing the information friction is crucial to the regulatory disclosure discussion because the recent literature postulates that more public information can benefit or harm welfare depending on the type of the disclosed information (Bond and Goldstein, 2015; Goldstein and Yang, 2019). Although structured products represent only one segment of the financial innovation market and alternative information types may cause information frictions in other segments (e.g., Piskorski et al., 2015), our analysis implies that the specific content of investor information provisions has direct implications on the structure of the financial innovation market. As this structure is crucial to financial stability (e.g., Gennaioli et al., 2012; Gorton and Metrick, 2012), our study should stimulate future research on the impact of information disclosure on the economy.

Appendix: Replication prices

We replicate each structured product by constructing a replicating portfolio of fixed-income and option instruments that has the same payout profile as the structured product.

We replicate Discount Certificates (DC) as

$$DC = \frac{M}{exp(rT)} - P(S - PV(D), M, T, \sigma_P), \tag{5}$$

where M is the redemption amount of the bond component, r is the interest rate, T is the product's time to maturity, and $P(S - PV(D), M, T, \sigma_P)$ is a put option on the underlying of the product strike M and time to maturity T. We adjust the spot price S by subtracting $PV(D)$, which is the present value of all IBES forecasted dividend payments during the lifetime of a product. σ_P is the implied volatility of the put option with corresponding strike and maturity.

We replicate a Barrier Discount Certificate (BDC) as

$$BDC = \frac{M}{exp(rT)} + C(S - PV(D), Y, T, \sigma_C) - DIP(S - PV(D), X, B, T, \sigma_{DIP}), \tag{6}$$

where M is the redemption amount of the bond component, r is the interest rate, T is the product's time to maturity, $C(S - PV(D), Y, T, \sigma_C)$ is a call option on the underlying of the product with strike Y, time to maturity T, and implied volatility σ_C, and $DIP(S - PV(D), X, B, T, \sigma_{DIP})$ is a down-and-in put option on the underlying of the product with strike X, barrier level B, time to maturity T, and implied volatility σ_{DIP}.

We replicate Reverse Convertibles (RC) as

$$RC = \frac{N}{exp(rT)} + \sum_{t_i \leq T} \frac{c_{t_i}}{exp(rt_i)} - \alpha P(S - PV(D), X, T, \sigma_P), \tag{7}$$

where N denotes the nominal amount, t_i are the coupon payment dates, c_{t_i} are the coupon payments at time t_i, and $P(S - PV(D), X, T, \sigma_P)$ is a put option on the underlying of the product with strike X, time to maturity T, and implied volatility σ_P. $\alpha = N/X$ reflects the number of put options contained in the nominal amount of one certificate.

We replicate Capped Outperformance Certificates (COC) as

$$\begin{aligned} COC = {} & \frac{M}{exp(rT)} - P(S - PV(D), M, T, \sigma_P) + \\ & (\alpha - 1)C(S - PV(D), Y, T, \sigma_{C1}) - (\alpha - 1)C(S - PV(D), M, T, \sigma_{C2}), \end{aligned} \tag{8}$$

where M is the redemption amount of the bond component, Y is the lower threshold of the underlying, above which the investor disproportionately participates in the performance of the underlying, α is the total participation rate between Y and M, $C(S - PV(D), Y, T, \sigma_{C1})$ is a call option with strike Y, time to maturity T and, implied volatility σ_{C1}. $C(S - PV(D), M, T, \sigma_{C2})$ is a call option with strike M.

We replicate Barrier Reverse Convertibles (BRC) as

$$BRC = \frac{N}{exp(rT)} + \sum_{t_i \leq T} \frac{c_{t_i}}{exp(rt_i)} - \alpha DIP(S - PV(D), X, B, T, \sigma_{DIP}), \tag{9}$$

where α is the number of put options contained in the nominal amount of one certificate, calculated as $\alpha = N/X$, and $DIP(S - PV(D), X, B, T, \sigma_{DIP})$ is a down-and-in put option on the underlying of the product with strike X, barrier B, time to maturity T, and implied volatility σ_{DIP}.

Finally, we construct Bonus Certificates (BC) using

$$\begin{aligned} BC = {} & \frac{M}{exp(rT)} + C(S - PV(D), M, T, \sigma_C) - \\ & P(S - PV(D), M, T, \sigma_P) + \alpha DOP(S - PV(D), M, B, T, \sigma_{DOP}), \end{aligned} \tag{10}$$

where M is the redemption amount of the bond component, α is the total participation rate, and $DOP(S - PV(D), X, B, T, \sigma_{DOP})$ is a down-and-out put option on the underlying of the product with strike M, barrier B, time to maturity T, and implied volatility σ_{DOP}.

We obtain the option components for a replication price by transforming traded (American) EUREX option prices into the (European) option prices of the structured product. For an accurate transformation, we need the forecasted dividend and implied volatility of the underlying as well as the pricing parameters provided in the term sheet of each product at the initial fixing date.

We collect consensus dividend forecasts from IBES. For each product, we use the IBES database's latest mean forecasted dividend entry prior to the initial fixing date to forecast the dividend amount paid during a product's lifetime. IBES does not provide ex-dividend date estimates. Thus, we estimate the future ex-dividend dates at each product's initial fixing date by projecting historical ex-dividend dates within a year prior to the initial fixing date into the future.

We extract implied volatilities from traded EUREX options. For each option contained in a structured product, we identify four corresponding EUREX options: one with the closest lower strike price and closest longer maturity, one with the closest lower strike price and closest shorter maturity, one with the closest higher strike price and closest longer maturity, and one with the closest higher strike price and closest shorter maturity. If we do not find all four options, we use the EUREX option that most closely matches the maturity and the strike price of a product's implicit option (e.g., Henderson and Pearson (2011)). As EUREX options are of the American type, we extract the implied volatility of each option using a binomial tree model based on Cox et al. (1979). We apply a daily discretization for the tree with $p = (e^{r(1/360)} - d)/(u - d)$, $q = 1 - p$, $u = e^{\sigma\sqrt{(1/360)}}$, and $d = 1/u$, in which p (q) is the probability of an increase (decrease), and u (d) is the discrete factor for an increase (decrease) in the stock price. We incorporate the discrete expected ex-dividend dates in the binomial tree. We obtain the implied volatility of an option by extracting the volatility in the tree that equates the tree's option price with the identified EUREX option's settlement price. Subsequently, we bi-linearly interpolate the implied volatilities of the four corresponding EUREX options based on their distance to the strike and the time to maturity of the option contained in the structured product.

For the interest rate, r, we follow the literature and use interpolated London Interbank Offered Rates (LIBOR) in the currency of the structured product for different maturities (Henderson and Pearson, 2011). For maturities beyond twelve months, we apply the corresponding swap rates. Since the maturity of a structured product rarely ever exactly matches the maturity of publicly available LIBOR rates, we linearly interpolate the LIBOR rates with the closest longer and shorter maturities for each product to estimate a maturity-matched interest rate.

Because the structured products in our sample entail only European type options, we apply the Black-Scholes formula to price the plain vanilla options contained in a product. We calculate barrier options using the formula in Hull (2009) for knock-in and knock-out options. We incorporate the forecasted dividends, implied volatility, and interest rate. The stock price that is relevant to calculating the replication price of structured products is $S - PV(D)$, in which S is the market price of the underlying at the initial fixing date and $PV(D)$ is the present value of the dividend payments forecasted to occur during a product's lifetime.

Figure A1: Historical Price Evolution

This figure depicts an excerpt of a product term sheet in our sample that shows the historical price evolution of the BMW AG share over the years before issuance.

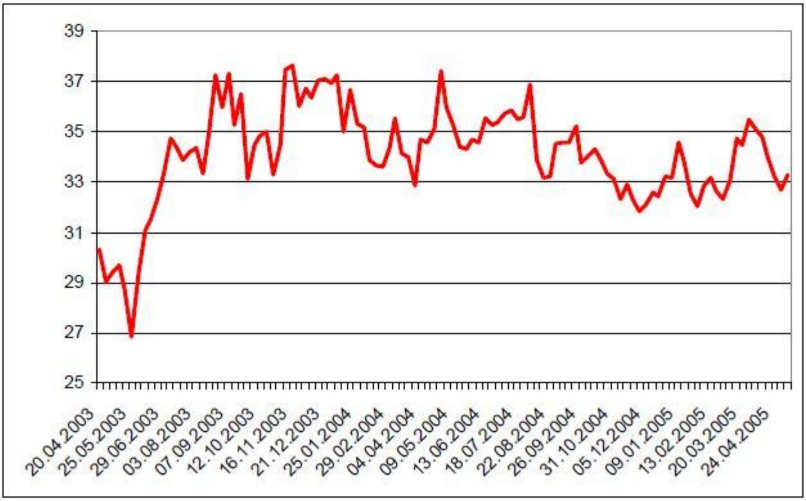

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Table 1
Overview of Structured Products Sample

This table presents the number of structured products in our sample grouped by issuer, product category, and year. Our starting point is a term sheets database containing all structured equity products issued in Switzerland from January 2005 through December 2010. From this database, we collect data on all products issued on a single equity underlying.

	Number of Issued Products
Panel A: By Issuer	
UBS	550
Goldman Sachs	144
Credit Suisse	136
Royal Bank of Scotland	134
Deutsche Bank	29
Merrill Lynch	11
J.P. Morgan	8
Panel B: By Product Category	
Discount Certificate	358
Barrier Reverse Convertible	295
Bonus Certificate	188
Reverse Convertible	97
Capped Outperformance Certificate	54
Barrier Discount Certificate	20
Panel C: By Year	
2005	73
2006	165
2007	249
2008	272
2009	178
2010	75

Table 2
Descriptive Statistics

This table presents descriptive statistics for our sample of structured products issued in Switzerland between January 2005 and December 2010 on a single equity underlying. Markup (*Markup*) is the issue price of a structured product minus its replication price, scaled by the issue price, expressed in percentage points. *Impl Vol* is the annualized implied volatility of the product's option on the underlying calculated for the lifetime of the product. We calculate *Hist Vol* as the standard deviation of a product underlying's returns over the 255 trading days before the initial fixing date. *Higher Vol* is a binary variable that is equal to one if *Impl Vol* is larger than *Hist Vol* and zero otherwise. *Forc Div* is the ratio between the present value of the forecasted dividend payments based on IBES that occur during the lifetime of a product and the stock price of the underlying at the initial fixing date. We define *Hist Div* as the ratio between the present value of the dividend payments that occur during the lifetime of a product estimated from the historical dividend payment pattern and the stock price of the underlying at the initial fixing date. *Higher Div* is a binary variable that is equal to one if *Forc Div* is larger than *Hist Div* and zero otherwise. *Market Cap* is the natural logarithm of the market value of equity of the underlying (in USDbn). *3m* and *12m Excess Return* are the 3- and 12-month continuous annual returns of the underlying in excess of the 3- and 12-month continuous annual returns of the Swiss Market Index (SMI), respectively. *1m* and *3m Turnover* are defined as the natural logarithm of the dollar value (in USDm) of the cumulated trading volume of the underlying over one month and three months prior to the issuance, respectively. We calculate *1m Call Volume* and *1m Put Volume* as the cumulated trading volume of EUREX call (put) options written on the underlying over one month preceding the initial fixing date divided by the volume of call (put) options written on all underlyings during the same time period. We calculate *Issuance Volume* as the natural logarithm of a structured product's issuance volume (in USD). *Vega* (*Delta*) is a product's annualized Vega (Delta) scaled by the product's initial value. *IVolatility* is a binary variable that is equal to one if, on the initial fixing date, a product's underlying is covered in the database of IVolatility.com and zero otherwise. *IBES Uncertainty* is the standard deviation of analysts' dividend forecasts for a stock. *Trading Size* is the logarithm of the average trading size in USD on the secondary market. *Features* is defined as the number of different features contained in a product's payoff formula based on the typology of features proposed by Célérier and Vallée (2017). We calculate *Impl Vol* 182 as the annualized implied volatility of an at-the-money put option with a maturity of 182 days on the product's underlying. *Time to Maturity* is defined as the number of business days between the initial fixing date and maturity date of a structured product.

	N	Mean	Std. Dev.	Q25	Median	Q75
Markup (in %)	1012	1.48	2.09	0.52	1.35	2.24
Impl Vol (in %)	1012	28.67	11.26	21.27	26.18	33.95
Hist Vol (in %)	1012	31.24	18.59	18.85	24.40	36.69
Higher Vol	1012	0.56	0.50	0	1	1
Forc Div (in %)	1012	2.73	2.18	1.13	2.51	3.81
Hist Div (in %)	1012	3.83	6.33	0.94	2.31	4.19
Higher Div	1012	0.60	0.49	0	1	1
Market Cap	1012	3.80	1.09	3.26	4.08	4.70
3m Excess Return (in %)	1012	1.46	11.09	-5.26	1.35	8.44
12m Excess Return (in %)	1012	0.87	21.26	-11.48	0.18	12.75
1m Turnover	1012	7.45	1.92	6.15	8.21	8.98
3m Turnover	1012	8.55	1.91	7.24	9.27	10.06
1m Call Option Volume (in %)	1012	2.63	3.79	0.31	1.66	3.13
1m Put Option Volume (in %)	1012	2.55	3.41	0.33	1.66	3.27
Issuance Volume	1012	15.73	1.021	15.00	15.84	16.55
Vega	1012	-0.46	0.29	-0.50	-0.44	-0.40
Delta	1012	1.56	1.84	0.48	0.96	1.92
IVolatility	1012	0.76	0.43	1	1	1
IBES Uncertainty	1012	0.38	0.53	0.09	0.24	0.43
Trading Size	783	10.71	1.15	9.98	10.68	11.33
Features	1012	2.12	0.90	1.00	2.00	3.00
Impl Vol 182 (in %)	994	31.19	14.73	21.65	28.32	37.46
Time to Maturity (trading days)	1012	294.16	150.80	249	255	265

Table 3
OLS Regressions of the Markups on Volatility Measures

This table presents results of OLS regressions. The dependent variable is the Markup (*Markup*), which is the issue price of a structured product minus its replication price, scaled by the issue price, expressed in percentage points. *Impl Vol* is the annualized implied volatility of the product's option on the underlying calculated for the lifetime of the product. We calculate *Hist Vol* as the standard deviation of a product underlying's returns over the 255 trading days before the initial fixing date. *Higher Vol* is a binary variable that is equal to one if *Impl Vol* is larger than *Hist Vol* and zero otherwise. *Vega* is defined as the product's annualized Vega scaled by its product's initial value. *IVolatility* is a binary variable that is equal to one if, on the initial fixing date, a product's underlying is covered in the database of IVolatility.com and zero otherwise. *Trading Size* is calculated as the logarithm of the average trading size in USD on the secondary market. The standard controls are defined in Table 2. We control for year fixed effects. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) Markup	(2) Markup	(3) Markup	(4) Markup	(5) Markup
Impl Vol	0.047***	0.038***	0.036***	0.038***	0.044***
	(6.12)	(4.93)	(4.74)	(4.98)	(6.00)
Higher Vol		1.006***	0.582**	1.413***	3.577***
		(6.70)	(2.29)	(5.35)	(3.11)
Vega			0.774***		
			(2.86)		
Higher Vol × Vega			-0.824*		
			(-1.92)		
IVolatility				0.175	
				(0.84)	
Higher Vol × IVolatility				-0.527*	
				(-1.85)	
Trading Size					0.039
					(0.45)
Higher Vol × Trading Size					-0.254**
					(-2.35)
Market Cap	0.171**	0.129*	0.126*	0.134*	0.116
	(2.34)	(1.79)	(1.75)	(1.85)	(1.64)
3m Excess Return	0.007	0.010*	0.011*	0.010*	-0.004
	(1.14)	(1.67)	(1.75)	(1.70)	(-0.62)
12m Excess Return	-0.004	-0.004	-0.004	-0.004	-0.000
	(-1.28)	(-1.25)	(-1.18)	(-1.35)	(-0.06)
1m Turnover	0.207	-0.076	-0.055	-0.051	0.311
	(0.72)	(-0.27)	(-0.19)	(-0.18)	(1.12)
3m Turnover	-0.246	0.047	0.029	0.020	-0.311
	(-0.85)	(0.16)	(0.10)	(0.07)	(-1.10)
1m Call Option Volume	-0.014	-0.002	-0.001	0.001	-0.036
	(-0.40)	(-0.06)	(-0.03)	(0.04)	(-0.83)
1m PutOption Volume	0.031	0.024	0.023	0.023	0.066
	(0.82)	(0.65)	(0.61)	(0.62)	(1.46)
Issuance Volume	-0.163**	-0.220***	-0.197***	-0.221***	-0.134*
	(-2.25)	(-3.09)	(-2.74)	(-3.10)	(-1.81)
Constant	2.787**	2.817**	2.859**	2.749**	1.251
	(2.09)	(2.15)	(2.18)	(2.10)	(0.86)
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1,012	1,012	1,012	1,012	783
R-squared	0.138	0.175	0.182	0.178	0.150

Table 4
OLS Regressions of the Markups on Dividend Measures

This table presents results of OLS regressions. The dependent variable is the Markup (*Markup*), which is the issue price of a structured product minus its replication price, scaled by the issue price, expressed in percentage points. *Forc Div* is the ratio between the present value of forecasted dividend payments based on IBES that occur during the lifetime of a product and the stock price of the underlying at the initial fixing date. We define *Hist Div* as the ratio between the present value of the dividend payments that occur during the lifetime of a product estimated from the historical dividend payment pattern and the stock price of the underlying at the initial fixing date. *Higher Div* is a binary variable that is equal to one if *Forc Div* is larger than *Hist Div* and zero otherwise. *Delta* is a product's annualized Delta scaled by the product's initial value. *IBES Uncertainty* is the standard deviation of analysts' dividend forecasts for a stock. *Trading Size* is calculated as the logarithm of the average trading size in USD on the secondary market. The standard controls are defined in Table 2. We control for year fixed effects. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) Markup	(2) Markup	(3) Markup	(4) Markup	(5) Markup
Forc Div	0.070**	-0.002	-0.084	0.009	-0.067*
	(2.23)	(-0.05)	(-0.02)	(0.27)	(-1.92)
Higher Div		0.768***	0.345*	0.977***	3.258***
		(5.12)	(1.93)	(5.68)	(2.73)
Delta			-0.206***		
			(-4.14)		
Higher Div × Delta			0.267***		
			(3.99)		
IBES Uncertainty				0.295*	
				(1.70)	
Higher Div × IBES Uncertainty				-0.584**	
				(-2.47)	
Trading Size					0.081
					(0.89)
Higher Div× Trading Size					-0.244**
					(-2.22)
Impl Vol	0.051***	0.058***	0.061***	0.057***	0.057***
	(6.47)	(7.33)	(7.82)	(7.21)	(7.49)
Market Cap	0.151**	0.099	0.107	0.076	0.109
	(2.05)	(1.35)	(1.46)	(0.99)	(1.51)
3m Excess Return	0.007	0.008	0.006	0.008	-0.004
	(1.12)	(1.26)	(1.03)	(1.32)	(-0.62)
12m Excess Return	-0.003	-0.004	-0.005	-0.004	-0.002
	(-0.90)	(-1.30)	(-1.43)	(-1.20)	(-0.53)
1m Turnover	0.242	0.227	0.253	0.209	0.502*
	(0.85)	(0.80)	(0.90)	(0.74)	(1.80)
3m Turnover	-0.277	-0.248	-0.268	-0.230	-0.495*
	(-0.96)	(-0.87)	(-0.95)	(-0.81)	(-1.75)
1m Call Option Volume	-0.008	-0.002	-0.010	-0.000	-0.042
	(-0.23)	(-0.07)	(-0.29)	(-0.00)	(-0.96)
1m Put Option Volume	0.021	0.014	0.021	0.011	0.068
	(0.54)	(0.37)	(0.55)	(0.28)	(1.47)
Issuance Volume	-0.169**	-0.151**	-0.142**	-0.136*	-0.072
	(-2.34)	(-2.12)	(-1.99)	(-1.89)	(-0.97)
Constant	2.756**	2.026	2.093	1.735	0.090
	(2.07)	(1.53)	(1.59)	(1.31)	(0.06)
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1,012	1,012	1,012	1,012	783
R-squared	0.142	0.164	0.180	0.169	0.134

Table 5
RD Design: Results for Products with Information Advantage

This table presents the regressions from a RD Design on the sample of products with a dividend information advantage ($Higher\ Div = 1$). The regression in Column (1) is estimated with the model defined in Eqn. (3). In Column (2), we extend Eqn. (3) with the terms of the second-order polynomial. The dependent variable is the Markup ($Markup$), which is the issue price of a structured product minus its replication price, scaled by the issue price, expressed in percentage points. $After$ is a dummy equal to one if the dividend announcement date closest to the initial fixing date occured on or after the product's initial fixing date and zero otherwise. We apply mean square error-optimal bandwidths and use heteroskedasticity-robust standard errors. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) Markup	(2) Markup
After	1.495***	1.283*
	(3.14)	(1.81)
Model	First-Order	Second-Order
Observations	198	229
R-squared	0.047	0.084

Table 6
RD Design: Refinements

This table presents the regressions from a RD Design for different subsamples. All regressions are estimated with the model defined in Eqn. (3). The dependent variable is the Markup ($Markup$), which is the issue price of a structured product minus its replication price, scaled by the issue price, expressed in percentage points. $After$ is a dummy equal to one if the dividend announcement date closest to the initial fixing date occured on or after the product's initial fixing date and zero otherwise. In Column (1), we use the subsample of products without a dividend information advantage ($Higher\ Div = 0$). In Column (2), we exclude all products for which the dividend announcement and earnings announcement are on the same day. In Column (3), we omit the products for which the IBES data was not updated between the dividend announcement date and the initial fixing date. In Column (4), we divide our sample into subsamples for which the abnormal trading volume of a product's underlying is below and above the sample median, respectively. We use heteroskedasticity-robust standard errors. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) Markup	(2) Markup	(3) Markup	(4) Markup	 Markup
	Without Adv.	Only Dividends	Only Updated	Abnormal Trading Volume Below	 Above
After	0.454	2.008*	2.567***	2.161**	1.040**
	(0.47)	(1.90)	(2.78)	(2.51)	(2.01)
Observations	57	30	156	96	102
R-squared	0.028	0.119	0.092	0.049	0.098

Table 7
OLS Regression of the Unexplained Performance

This table presents results using an OLS regression. The dependent variable is *Product Performance*, which is the annualized ex-post performance of a structured product calculated as the return of the final payoff over the issue price. *Return Underlying* is the annualized ex-post total return of the product's underlying multiplied by *Delta*. We use Product Category fixed effects, as well as the interactions between these fixed effects and *Return Underlying* and *Return Underlying Squared*, respectively. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) Product Performance
Return Underlying	0.429***
	(3.72)
Return Underlying Squared	-1.221***
	(-5.01)
Product Category FE	Yes
Product Category FE Interactions	Yes
Observations	1012
R-squared	0.938

Table 8
RD Design: Results with Unexplained Performance

This table presents the regressions from a RD Design on the sample of products with a dividend information advantage ($Higher\ Div = 1$). The regression in Column (1) is estimated with the model defined in Eqn. (3). In Column (2), we extend Eqn. (3) with the terms of the second-order polynomial. The dependent variable is the unexplained performance (UP), which is defined as the residuals of the model in Eqn. (4). $After$ is a dummy equal to one if the dividend announcement date closest to the initial fixing date occured on or after the product's initial fixing date and zero otherwise. We apply mean square error-optimal bandwidths and use heteroskedasticity-robust standard errors. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) UP	(2) UP
After	-0.030*	-0.042*
	(-1.69)	(-1.65)
Model	First-Order	Second-Order
Observations	227	247
R-squared	0.052	0.074

Table 9
Nearest Neighbor Matching

This table presents results of the Nearest Neighbor matching approach. For each underlying that issuers actually choose for a structured product, we select the five non-chosen underlyings that are closest neighbors with respect to the Mahalanobis distance. The matching variables are the underlying's market capitalization, the 3- and 12-month excess returns, the one-month and three-month cumulated trading volumes as well as the relative one-month call (put) volume written on the underlying. We also require that the matched underlyings are listed in the same *Corresponding Index* and belong to the same *Industry*. *Corresponding Index* is the index of the underlying. We define *Industry* as the two-digit SIC code. *Higher Vol* (*Higher Div*) is a binary variable that is equal to one if *Impl Vol* (*Forc Div*) is larger than *Hist Vol* (*Hist Div*) and zero otherwise. *Mean Difference Higher Vol* (*Mean Difference Impl Vol*) is calculated as the difference between the value of *Higher Vol* (*Impl Vol*) of the underlying that is actually chosen and the mean value of *Higher Vol* (*Impl Vol*) of the matched underlyings. *Mean Difference Higher Div* (*Mean Difference Forc Div*) is calculated as the difference between the value of *Higher Div* (*Forc Div*) of the underlying that is actually chosen and the mean value of *Higher Div* (*Forc Div*) of the matched underlyings. Depending on the specification of the model, the matching variables are lagged by one, two, and three weeks. The standard controls are defined in Table 2. p-values of the one-sided t-test are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A:	(1)	(2)	(3)
Lag	3 Weeks	2 Weeks	1 Week
Mean Higher Vol Issued	0.615	0.598	0.584
Mean Higher Vol Matched	0.569	0.560	0.556
Mean Difference Higher Vol	0.046**	0.038*	0.029
	(0.03)	(0.05)	(0.11)
Mean Higher Div Issued	0.703	0.701	0.697
Mean Higher Div Matched	0.644	0.637	0.630
Mean Difference Higher Div	0.059***	0.064***	0.067***
	(0.00)	(0.00)	(0.00)

Panel B:	(1)	(2)	(3)
Lag	3 Weeks	2 Weeks	1 Week
Mean Impl Vol Issued	29.338	29.247	29.176
Mean Imp Vol Matched	28.833	28.810	28.787
Mean Difference Impl Vol	0.505	0.438	0.389
	(0.20)	(0.22)	(0.25)
Mean Forc Div Issued	2.999	2.956	2.972
Mean Forc Div Matched	2.847	2.774	2.769
Mean Difference Forc Div	0.152	0.287	0.203*
	(0.15)	(0.10)	(0.08)

Table 10
Robustness Tests: Volatility Measures

This table presents various robustness tests for our volatility regression results. The dependent variable is the Markup ($Markup$), which is the issue price of a structured product minus its replication price, scaled by the issue price, expressed in percentage points. $Impl\ Vol$ is the annualized implied volatility of the product's option on the underlying calculated for the lifetime of the product. $Higher\ Vol$ is a binary variable that is equal to one if $Impl\ Vol$ is larger than $Hist\ Vol$ and zero otherwise. We calculate $Hist\ Vol$ as the standard deviation of a product underlying's returns over the 255 trading days before the initial fixing date. $Impl\ Vol\ Squared$ is calculated as the square product of $Impl\ Vol$. $Higher\ Div$ is a binary variable that is equal to one if $Forc\ Div$ is larger than $Hist\ Div$ and zero otherwise. $Impl\ Vol$ 182 is the annualized implied volatility of an at-the-money put option on the product's underlying with a maturity of 182 days. $Higher\ Vol$ 182 is a binary variable that is equal to one if $Impl\ Vol$ 182 is larger than $Hist\ Vol$ and zero otherwise. $Higher\ Vol$ 162 is a binary variable that is equal to one if $Impl\ Vol$ is larger than the standard deviation of a product underlying's returns over the 162 trading days before the initial fixing date and zero otherwise. $Vol\ Difference$ is the difference between $Impl\ Vol$ and $Hist\ Vol$. We include the same standard control variables as in Table 3 and control for year fixed effects. Depending on the specification of the regression, we additionally control for product category, issuer, and underlying fixed effects. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) Markup	(2) Markup	(3) Markup	(4) Markup	(5) Markup	(6) Markup
Impl Vol	0.203***		0.054***	0.048***	0.058***	0.050***
	(6.91)		(7.04)	(6.27)	(7.95)	(3.34)
Higher Vol	0.888***				1.084***	0.919***
	(5.95)				(7.91)	(4.79)
Impl Vol Squared	-0.002***					
	(-5.43)					
Impl Vol 182		-0.002				
		(-0.30)				
Higher Vol 182		0.670***				
		(4.08)				
Higher Vol 162			0.943***			
			(6.42)			
Vol Difference				0.064***		
				(8.26)		
Forc Div	0.046	-0.027	0.022	-0.024	0.023	0.089
	(1.39)	(-0.76)	(0.66)	(-0.73)	(0.74)	(1.55)
Higher Div	0.788***	0.546***	0.698***	0.793***	0.236*	0.695***
	(5.38)	(3.54)	(4.74)	(5.46)	(1.73)	(3.70)
Constant	-1.357	4.125***	1.461	3.787***	1.373	3.833
	(-0.95)	(3.07)	(1.12)	(2.91)	(0.85)	(1.36)
Standard Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Product Category FE	No	No	No	No	Yes	No
Issuer FE	No	No	No	No	Yes	No
Underlying FE	No	No	No	No	No	Yes
Underlying Cluster SE	No	No	No	No	No	Yes
Observations	1,012	994	1,012	1,012	1,012	1,012
R-squared	0.223	0.133	0.197	0.218	0.365	0.315

Table 11
Robustness Tests: Dividend Measures

This table presents various robustness tests for our dividend regression results. The dependent variable is the Markup ($Markup$), which is the issue price of a structured product minus its replication price, scaled by the issue price, expressed in percentage points. $Forc\ Div$ is the ratio between the present value of forecasted dividend payments based on IBES that occur during the lifetime of a product and the stock price of the underlying at the initial fixing date. $Higher\ Div$ is a binary variable that is equal to one if $Forc\ Div$ is larger than $Hist\ Div$ and zero otherwise. $Forc\ Div\ Squared$ is the square product of $Forc\ Div$. $Div\ Difference$ is defined as the difference between $Forc\ Div$ and $Hist\ Div$. $Impl\ Vol$ is the annualized implied volatility of the product's option on the underlying calculated for the lifetime of the product. $Higher\ Vol$ is a binary variable that is equal to one if $Impl\ Vol$ is larger than $Hist\ Vol$ and zero otherwise. We calculate $Hist\ Vol$ as the standard deviation of a product underlying's returns over the 255 trading days before the initial fixing date. $HH-Index$ is defined as the Herfindal-Hirshman-Index calculated based on the issuers' market share in the number of products at the initial fixing date. We calculate $Funding\ Needs$ as the quarterly ratio of deposits to assets. $CDS\ Spread$ is the CDS spread of the issuer at the initial fixing date. $Economic\ Environment$ is the Economic Barometer published by the KOF Swiss Economic Institute. $Time\ to\ Maturity$ is the product maturity in years. $Short-term\ Product$ is a binary variable that is equal to one if $Time\ to\ Maturity$ is smaller or equal to one year and zero otherwise. $Features$ is defined as the number of different features contained in a product's payoff formula based on the typology of features proposed by Célérier and Vallée (2017). $VSMI$ is an index based on the implied volatilities of SMI options across maturities. We include the same standard control variables as in Table 4 and control for year fixed effects. Depending on the specification of the regression, we additionally control for product category, issuer, and underlying fixed effects. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) Markup	(2) Markup	(3) Markup	(4) Markup	(5) Markup
Forc Div	0.032	0.085***	0.023	0.089	0.060*
	(0.36)	(2.75)	(0.74)	(1.55)	(1.72)
Higher Div	0.683***		0.236*	0.695***	0.371**
	(4.40)		(1.73)	(3.70)	(2.50)
Forc Div Squared	0.000				
	(0.01)				
Div Difference		0.041***			
		(4.12)			
Hist Div					-0.008
					(-0.76)
Hist Vol					-0.077***
					(-8.65)
HH-Index					1.488
					(0.57)
Funding Needs					3.550**
					(2.12)
CDS Spread					0.112
					(0.65)
Economic Environment					0.034***
					(3.03)
Time to Maturity					0.866***
					(4.83)
Short-term Product					0.177
					(0.67)
Features					0.511***
					(5.71)
VSMI					-0.042***
					(-2.75)
Impl Vol	0.049***	0.047***	0.058***	0.050***	0.146***
	(6.27)	(6.05)	(7.95)	(3.34)	(11.15)
Higher Vol	1.008***	1.059***	1.084***	0.919***	0.415**
	(6.73)	(7.08)	(7.91)	(4.79)	(2.54)
Constant	2.124	1.937	1.373	3.833	-8.582***
	(1.63)	(1.48)	(0.85)	(1.36)	(-4.11)
Standard Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Product Category FE	No	No	Yes	No	No
Issuer FE	No	No	Yes	No	No
Underlying FE	No	No	No	Yes	No
Underlying Cluster SE	No	No	No	Yes	No
Observations	1,012	1,012	1,012	1,012	1,012
R-squared	0.200	0.197	0.365	0.315	0.347

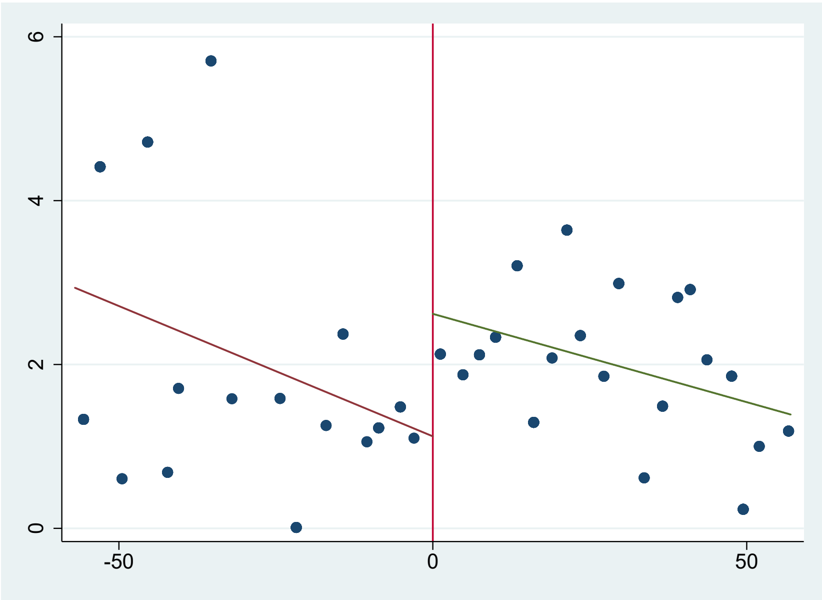

Figure 1
RD: Markup

This figure shows the distribution of the markup ($Markup$) in a time window of [-57, 57] days around the threshold. We define the x-axis variable as the difference between the dividend announcement date closest to the initial fixing date and the initial fixing date measured in days. A negative (positive) value indicates that the dividend announcement date occurs before (after) the initial fixing date date. We fit a linear function on either side of the zero-threshold using binwidths of 3 days. Each bin represents the average of the $Markup$s over 3 days. We use the subsample of products with a dividend information advantage ($Higher\ Div = 1$).

Obfuscation through Complexity: Evidence from the Market for Retail Financial Products*

Simon Straumann†

Abstract

This paper examines the role of obfuscation in financial innovations. By exploiting the staggered adoption of a price disclosure policy for issuers of retail structured products, I show that issuers subject to price disclosure significantly increase the complexity of their products over time. This finding is further confirmed in a difference-in-difference-in-differences setting. Moreover, complexity significantly reduces the price elasticity of demand, thus raising the concern that complexity induces social welfare costs. Overall, these findings are consistent with the model predictions of Carlin and Manso (2010) on strategic obfuscation activities of financial institutions.

JEL-Code: D12, G24, G28, L15

Keywords: Structured products, complexity, obfuscation, demand elasticities

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1 Introduction

It is well documented that in many markets, consumers often fail to find the best alternative when faced with several options.[1] Financial markets are no exception (Barber and Odean, 2013; Egan, 2019; Shiller, 2003). Even for simple and homogenous financial products such as index mutual funds, investors frequently fail to choose the product with the lowest fees (Choi et al., 2009; Hortaçsu and Syverson, 2004). Empirical evidence suggests that financial institutions further complicate product search by engaging in strategic obfuscation activities such as deceptive advertisements, complexity, biased advice, or information misrepresentation in order to maximize their profits (Gurun et al., 2016; Célérier and Vallée, 2017; Egan, 2019; Hastings et al., 2017; Hoechle et al., 2018; Piskorski et al., 2015). More importantly, obfuscation serves not only as a way for financial institutions to extract investors' surplus but can cause significant welfare costs, for example, by increasing the incidence of investment mistakes and discouraging investors from participating in the financial markets (Carlin and Manso, 2010; Campbell, 2006; Calvet et al., 2007; Zingales, 2015). Therefore, understanding the dynamics of strategic obfuscation is crucial for social welfare optimization.

One of the most comprehensive models on obfuscation in the financial markets is the one by Carlin and Manso (2010). In a dynamic framework, their model rationalizes an increase in obfuscation activities of financial institutions as a potential best response to more facilitated learning for investors, for example, through investor education. This insight has important implications for policymakers because it suggests that educational initiatives or disclosure policies intending to educate and protect investors can, contrary to their purpose, induce more obfuscation in the financial system and thus potentially harm social welfare. This is the first study to test the model empirically, and thereby,

[1]For examples, see Ellison and Ellison (2009); Hossain and Morgan (2006); Brown et al. (2010) for computer accessories and electronics, Kling et al. (2012) for prescription drug plans, Chetty et al. (2009) for groceries, Bronnenberg et al. (2015) for medical drugs, Clay et al. (2001) for books, Busse et al. (2013) for cars, and Dahlquist et al. (2018) for pension plans.

provide more insights into the dynamics and consequences of strategic obfuscation.

This paper focuses on obfuscation through product complexity in the market for retail structured products. The theoretical literature agrees that complexity can obfuscate the comparability of products and increase the difficulty to find the most suitable product (Chioveanu and Zhou, 2013; Wilson, 2010; Piccione and Spiegler, 2012). Moreover, the findings of experimental studies show that complexity induces more suboptimal investment choices (Gabaix et al., 2006; Kalaycı and Potters, 2011; Kalaycı, 2015, 2016). While the theoretical framework is well established, and experiments show a link between complexity and suboptimal investment choices, evidence from the field is lacking due to several empirical challenges. The setting of this paper alows me to address these challenges. First, it is difficult to measure complexity quantitatively. Since payoff formulas of structured products are clearly specified and set before issuance, observing a product's payoff formula enables me to determine its complexity based on a simple approach. To this end, I follow the methodology of Célérier and Vallée (2017) and define complexity as the number of features embedded in a product. The idea is that each feature adds one dimension to a product's payoff formula, and thus increases the difficulty to understand the product and to compare it with others. Second, financial products often differ in several observable and unobservable characteristics other than complexity, and therefore comparing products is not straightforward. As structured products are completely characterized by a limited set of observable parameters, I can directly compare products along all relevant dimensions. Third, due to missing control groups, inferences from analyses often suffer from an omitted variables bias. The empirical setting allows me also to incorporate a control group and thus helps to capture a major part of the unobserved variation.

In the first part of the paper, I test whether issuers engage more in obfuscation activities when learning by investors is facilitated. To this end, I analyze the changes in product complexity around the introduction of a price disclosure policy in the market for structured products. This policy enables investors to learn about prices, which simplifies product comparability and facilitates more sophisticated investment decisions (Carlin and Manso, 2010; Ellison and Wolitzky, 2012; Piccione and Spiegler, 2012). Also, investors can learn over time, for example, through repeatedly participating in the market or through social interaction, and thus gradually become more proficient (Duffie and Manso, 2007; Duffie et al., 2009; Feng and Seasholes, 2005; Seru et al., 2009).[2] This paper exploits the staggered adoption of a price disclosure policy for issuers of retail structured products to analyze their reaction to more facilitated learning by investors. The empirical setting allows me to measure the changes in product complexity on the issuer level and over time in a dynamic difference-in-differences framework. I find hat issuers committed to price transparency start to steadily increase the complexity of their products. Already within two months after an issuer starts to disclose prices, the number of features added to a product increases on average by 0.13 compared to the control group consisting of products of non-disclosing issuers. This effect more than doubles for products issued nine or more months after the adoption of the policy. This impact is economically meaningful. The change in complexity corresponds to an increase in added features to the standard product specification of 4.3% within two months and 9.3% after nine or more months. Finally, I show that obfuscation is positively correlated with the level of competition. This finding provides new insights into the ongoing debate on whether competition increases or decreases obfuscation intensity.

The choice of an issuer to disclose is voluntary, and therefore raises the concern that disclosing and non-disclosing issuers are systematically different. The claim of a causal effect of price disclosure on complexity is invalid if there exists an unobserved variable that is positively correlated with an issuer's decision to start disclosing and an increase in product complexity. I address this potential endogeneity problem by providing evidence that the parallel trends assumption holds. Also, I employ a difference-in-difference-in-

[2]For an extensive literature review on learning in the financial markets, please refer to Pastor and Veronesi (2009).

differences approach to control for issuer-specific time-variant variables. The findings are robust to this additional analysis.

In the second part of the paper, I test whether complexity serves as an obfuscation mechanism for issuers to reduce the price sensitivity of investors. Estimating demand functions is challenging because prices are usually determined by both the demand and supply side. The setting allows me to avoid this endogeneity problem because the price and all other parameters of a product are set prior issuance and supply is fully elastic. Moreover, since products are completely characterized by a limited set of observable parameters, I can define distinct markets consisting of comparable products, and thus implicitly control for variables that are constant within markets. I make use of a well-specified demand model, including all observable parameters that fully characterize a product as well as market fixed effects that capture virtually all unobservable variation to determine the effect of complexity on the price sensitivity.

The results reveal a significant impact of complexity on the price elasticity of demand. As shown in the first part of the analysis, issuers with price disclosure add within two months on average 0.13 features more to their products relative to the control group. Such an increase of 0.13 features corresponds to a reduction in the price sensitivity of demand for a standard product by approximately 15%. I discuss alternative explanations for this finding. An empirical analysis confirms that the results are not driven by misaligned incentives for brokers (Egan, 2019) or a systematically stronger inflow of new investors to more complex products due to price disclosure (Moraga-González et al., 2017). The alternative explanation that price disclosure crowds out more sophisticated investors in markets with higher complexity, however, is not clearly rejected by the data (Ellison, 2005; Gabaix and Laibson, 2006).

This paper contributes to three streams of the literature. First, this work adds to the literature on strategic obfuscation activities (Carlin and Manso, 2010; Carlin, 2009; Chioveanu and Zhou, 2013; Ellison, 2005; Ellison and Ellison, 2009; Ellison and Wolitzky, 2012; Gabaix and Laibson, 2006; Spiegler, 2006, 2016). The current paper relates to the empirical work of Ellison and Ellison (2009) that examines obfuscation activities of internet retail sellers in the presence of an online price search engine that should help consumers to compare products. In contrast to Ellison and Ellison (2009), this study analyzes strategic obfuscation activities in a dynamic setting where the focus is on the reaction of the issuers to investor learning. The empirical findings suggest that issuers subject to price transparency steadily increase product complexity, and thereby making product comparability more difficult for investors.

This study also adds the literature on the effects of complexity (Carlin et al., 2013; Chioveanu and Zhou, 2013; Kalaycı and Potters, 2011; Kalaycı, 2015, 2016; Piccione and Spiegler, 2012; Wilson, 2010). Célérier and Vallée (2017) show empirically that more complex structured products are more expensive, exhibit lower ex-post performance, and are subject to higher risks. Similarly, the study of Ghent et al. (2017) analyzes the market for mortgage-backed securities and finds that complexity is associated with higher default probability and lower realized return. The present study complements this literature by empirically establishing a link between higher levels of complexity and lower price sensitivity of demand.

Finally, this paper contributes to the stream of literature on the effects of information disclosure (Agarwal et al., 2015; Goldstein and Yang, 2019; Hermalin and Weisbach, 2012; Hellwig and Veldkamp, 2009; Morris and Shin, 2002). Several studies stress the adverse effects of information disclosure such as a decrease in performance of more informed funds or more firm financial distress (Agarwal et al., 2015; Hertzberg et al., 2011; James and Lawler, 2011; Lacko and Pappalardo, 2010; Morris and Shin, 2002), whereas other papers focus on the positive consequences of information disclosure (Fishman and Hagerty, 2003; Svensson, 2006). The documented reduction in investor price sensitivity due to an increase in complexity highlights a negative (side) effect of information disclosure.

The remainder of this paper is structured as follows. Section 2 describes the market structure and the disclosure policy. Section 3 presents the dataset, the empirical approach, and the results. Section 4 reports the results from the demand estimation, and Section 5 discusses alternative explanations of the findings. Lastly, Section 6 concludes.

2 Market Structure and Disclosure Policy

This study analyzes the market for retail structured products in Switzerland. Structured products are financial instruments linked to the performance of one or more underlyings. A typical structured product consists of one or more derivative instruments in combination with a stock or bond position. During the last decade, the global market for structured products has grown considerably (Calvet et al., 2018; Célérier and Vallée, 2017; Egan, 2019). Based on the volume invested in structured products, Switzerland is one of the largest markets worldwide. By the end of 2017, investors in Switzerland held more than 200bn CHF worth of outstanding structured products in their custody accounts.[3] This amount corresponds to around 20% of total assets under management of mutual funds in Switzerland.[4] All households in Switzerland have access to the retail structured product markets and the minimum investment amount is usually around 1'000 CHF.

This paper examines the effects of a voluntary disclosure policy of issuers in Switzerland. The adoption of the disclosure policy occurred in two waves. As of October 2014, three issuers (EFG International, Leonteq, and Vontobel) started to disclose the total expense ratio (TER) for their newly issued products. TER is defined as the difference between the nominal and the market value of a product, adjusted for the product's time to maturity and expressed in percentage of the nominal. Therefore, TER measures the yearly total costs of a product to the investor, including all structuring costs as well as the issuer's profit margin. Because it is expressed as a percentage of the product's nom-

[3] See `https://data.snb.ch/en/topics/banken/`

[4] See `https://www.swissfunddata.ch/sfdpub/en/market/providersArchive`

inal value, TER can be directly interpreted as the price of the product and allows direct comparison between products. In addition to the TER, issuers also disclose a product's distribution fees. These costs are included in TER and cover all commissions paid to brokers and other financial intermediaries. It is important to note that issuers only committed to disclosing the price at issuance, thus the product is only price transparent on the primary market. Therefore, the analysis focuses on products at issuance. While the exact strategic intentions for the adoption of the price disclosure policy are unknown, Vontobel states their reasons for the decision to disclose as a way to "create further trust among investors" and to provide "additional guidance to help them in reaching their investment decisions".[5] Starting in March 2015, two additional issuers (Zurich Cantonal Bank and Notenstein) also decided to adopt the transparency policy.

3 Data and Empirical Strategy

3.1 Data

The data set is provided by Derivative Partners and contains all retail structured products issued in Switzerland between May 2014 and March 2016. In this study, I focus on barrier reverse convertibles (BRC) because they are the predominant product category in Switzerland. During the sample period, more than 70% of the issued products are BRCs. Also, a within product category analysis mitigates the concern of a heterogeneous effect of complexity on different product categories, for example, adding one particular feature to a product might have a different effect depending on the product category.

BRCs are yield-enhancement products that are advertised to provide investors with high returns. As displayed in Figure 1, an investor of a BRC gives up the participation in the positive performance of the underlying in exchange for a coupon. The coupon rate

[5] See `https://www.vontobel.com/en-ch/about-vontobel/media/communications/vontobel-creates-comprehensive-cost-transparency-for-structured-products/`

is usually significantly higher than the current market rates. In addition, a BRC offers a conditional downside protection.

A standard BRC is characterized by the underlying, a time to maturity, a fixed coupon that is either paid out semi-annually or annually, and a conditional capital protection barrier. While the coupon is paid in any case, the capital protection depends on the performance of the underlying. If the underlying never breaches the pre-specified barrier during the lifetime of a product, the invested amount is fully paid back. On the other hand, if the barrier is breached once during the lifetime of a product, the capital protection is lost. In the case of a barrier breach, the final payoff is based on the difference between the underlying reference price at issuance and at maturity, while the maximum payoff is capped at the invested amount. A BRC is replicated with a position in a short down-and-in put option and a cash-equivalent position that is equal to the present value of the invested amount and all expected coupon payments. All else equal, a product with a higher coupon (lower barrier) is more attractive for the investor.

INSERT FIGURE 1 NEAR HERE

The initial sample consists of 12'737 BRCs. I exclude products with missing term-sheets and without maturity date (so-called open-end products). Further, I restrict the sample to products for which information on the issuance volume is available. The final sample consists of 12'342 BRCs issued by 17 different issuers with a total issuance volume of over 188bn CHF. Table 1 presents an overview of the most occurring product characteristics in the sample, and Table 2 reports the summary statistics. Out of all issuers, Vontobel, Leonteq, and Julius Baer issued the most products during the sample period. The time to maturity of BRCs is standardized. More than 57% of the products have a time to maturity of one year, whereas around 14% and 12% of the products have a time to maturity of 1.5 and two years, respectively.

The major share of products in the sample are issued in CHF (59%), EUR (22%), and USD (17%). Around 98% of the products participate in the performance of equities, of which 68% are linked to multiple stocks and 31% to single stocks.[6] The most common single stock underlyings are constituents of the Swiss stock market index (SMI), and the most common combinations of multiple underlyings are Euro Stoxx 50 / S&P 500 / SMI and Nestlé / Novartis / Roche.

As shown in Table 2, the average TER in the sample amounts to 1.68%. The TERs disclosed by the issuers are based on their calculations, thus raising the concern that the published information is biased in favor of the issuer. The recent studies of Vokata (2018) for the US market and of Bauer et al. (2016) for the German market, however, show that prices disclosed by issuers are close to those calculated based on academic pricing models. Also, the average TER is similar in magnitude as prices found in other studies for the Swiss market using academic pricing models (Ammann et al., 2019; Maringer et al., 2016). This finding provides further evidence for the validity of the disclosed TER.

3.2 Complexity

For the construction of the complexity measure, I follow the methodology of Célérier and Vallée (2017).[7] Célérier and Vallée define their main measure of complexity as the number of features embedded in a product. According to their typology, products can exhibit one main feature and up to seven additional features. Table 3 provides an overview of the features and their rates of occurrence in the data sample. The standard BRC consists of a main feature and two additional features (*Increased Downside* and *Exotic Condition*). Therefore, the standard BRCs exhibits a complexity level of three. Issuers often extend the products with an *Underlying Selection* feature. Compared to the standard BRC, the payoff of these products depends on the performance of more than one underlying. The products in the data sample are also frequently enhanced with an *Early Redemption* feature. BRCs with an *Early Redemption* feature comprise an option

[6] The remaining products are linked to baskets.

[7] For a comprehensive explanation of all features, please refer to the online appendix of Célérier and Vallée (2017).

that allows the issuer to recall the product before its final maturity date in exchange for a pre-determined redemption payment. The *Early Redemption* feature frequently added to BRCs exists in two variations. Products with an embedded *Auto Call* are redeemed as soon as an explicitly specified underlying price level is reached, whereas the *Hard Call* feature allows issuers to redeem a product independent of the underlying price level. As shown in Columns (2) and (3) of Table 3, products with price disclosure exhibit proportionally more *Underlying Selection* features (66.31% and 69.50%) while a similar share of products contain an *Early Redemption* feature (35.06% and 35.65%).

Moreover, I consider two additional features that are not captured by the typology of Célérier and Vallée (2017) but are common in products issued in Switzerland.[8] First, around 18.18% of the products exhibit a *Quanto* feature. Products with a *Quanto* feature embed an additional derivative that hedges the investor against exchange rate fluctuations between the product's currency and its underlying(s). The costs of this hedge have a direct impact on a product's price. Second, 1.56% of the products are collateralized (*Collateral Secured*). Due to the collateralization, these products exhibit minimal credit issuer risk but also higher costs. As shown in Columns (2) and (3) of Table 3, both features are used more often in products with price disclosure.

The following example illustrates the approach to determine a product's level of complexity. Figure 2 displays excerpts of two product term sheets. Product 1 represents a standard BRC that contains only three features. Product 2 exhibits several additional features. First, the product is linked to the performance of multiple underlyings, thus also includes a *Underlying Selection* feature. Second, the product is autocallable, which adds an *Early Redemption* feature. Finally, since the product is currency-hedged, it also contains a *Quanto* feature. In total, Product 2 exhibits six features, whereas Product 1 contains only three features, making Product 2 based on the methodology considerably more complex.

[8]The results remain qualitatively the same if I construct the complexity measure without the additional features but include them as explanatory variables.

INSERT FIGURE 2 NEAR HERE

Figure 3 displays the relative frequency of the levels of complexity for non-disclosing and disclosing issuers. The differences between the distributions already indicate that products of disclosing issuers are more complex. As shown in the figure, products of non-disclosing issuers exhibit more frequently the standard number of features whereas a large share of the products of disclosing issuers exhibit six features.[9]

INSERT FIGURE 3 NEAR HERE

Products in the sample contain on average 4.21 features, indicating that issuers add on average 1.21 features to the standard BRC.[10] In comparison to Célérier and Vallée (2017) who find an average complexity measure of 2.50 for retail structured products issued in 16 European countries (without Switzerland) between 2002 and 2010, the level of complexity in the sample is high. Two factors most likely drive the difference in complexity between the two studies. First, the sample period of Célérier and Vallée (2017) spans over nine years and ends in 2010. As the authors find that product complexity has significantly increased over time, the products with lower complexity issued at the beginning of the observation period draw the sample average downwards. Also, product complexity could have increased between the end of their sample period and the start of the sample period of this paper. Second, I focus on one particular group of products, which, by construction, exhibit multiple features.

3.3 Disclosure and Complexity

For the empirical analysis, I employ a dynamic difference-in-differences model in the spirit of Stevenson and Wolfers (2006). Using the data described in Section 3.1, I estimate the

[9]The sample contains a few products with two features. For these products, only the price of the underlying at maturity is relevant for the final payoff. Therefore, they are not path-dependent and exhibit one feature less (*Exotic Condition*) compared to the standard product.

[10]If I exclude *Quanto* and *Collateral Secured* from the list of possible features, this number drops to 4.03.

following regression model:

$$Features_{i,j,t} = \alpha_0 + \sum_m \beta_m Disclosure^m_{j,t} + Controls_{i,j,t} + FixedEffects_{j,t} + \epsilon_{i,j,t}, \quad (1)$$

where $Features$ is the number of features embedded in product i based on the approach described in Section 3.2. $Disclosure^m$ is a set of dummy variables that are equal to one if issuer j of product i had started to disclose m months ago. The whole set of dummy variables is equal to zero for issuers that never disclose during the whole sample period. The estimated coefficients of $Disclosure^m$ capture the dynamics in complexity following issuer j's decision to disclose. If issuers start to indroduce more product complexity in response to investor learning facilitated by price disclosure, β_m should be positive and increasing in m.

A major identification challenge is potential omitted variables that are correlated with both product complexity and the explanatory variables. The empirical setting of the analysis allows me to address this concern in several ways. First, I include year-month fixed effects and issuer fixed effects to control for variables that are either constant across issuer or over time within issuer. The absorbed variation of the two fixed effects is substantial as the R^2 drops by 17 percentage points if I exclude both the issuer and year-month dummies from the main regression specification in Column (1) of Table 4. Second, non-disclosing issuers serve as counterfactual, thus absorbing all variation that is common to treated and untreated issuers, such as changes in the market environment and economic-wide shocks. Third, I include several additional explanatory variables. Following Célérier and Vallée (2017), I control for a product i's time to maturity (measured in years) and underlying asset class (equity, interest rates, exchange rates, commodities, or others). Further, I include variables to control for issuance volume (measured in CHF) and competition. I define competition as the number of products issued in month t by all issuers other than issuer j.

An identification challenge that is related to the omitted variables problem arises because issuers can freely decide whether and when to start disclosing. This treatment endogeneity is of concern if there exist one or more unobserved variables that determine both the decision to disclose and the changes in product complexity. Not addressing this issue could render the causal claim between price disclosure and complexity invalid. The empirical approach allows me to tackle this problem in multiple ways. First, Eqn. (1) captures all systematic differences across issuers, as well as between treated and untreated issuers. Therefore, unobserved issuer characteristics that are associated with the decision to disclose but are constant over the whole sample period or change in parallel to the control group are absorbed by explanatory variables. Second, I show that the parallel trends assumption holds. This result suggests that there are most likely no unobserved time-variant discloser-specific characteristics associated with the decision to disclose and the changes in complexity before price disclosure. Third, I present an extended analysis employing a difference-in-difference-in-differences approach (triple differences). To this end, I exploit that some issuers in the data sample are also issuing products in the German market. While the German market is very similar to the Swiss market in terms of product offering and market environment, products issued in Germany are unaffected by the disclosure decision in the Swiss market. Therefore, the changes in complexity in the German market provide an ideal counterfactual to the treatment in the Swiss market. This approach allows me to also absorb time-variant variables that are related to the disclosure decision but are constant within the issuer across countries and thus, lends further credibility to the causal link between price disclosure and an increase in complexity.

One final empirical concern is that the standard errors estimated in the difference-in-differences setting are biased in the presence of correlation within groups and time periods (Bertrand et al., 2004; Donald and Lang, 2007). As shown by Bertrand et al. (2004), clustering the standard errors reduces this bias. Therefore, I calculate standard errors that are clustered at the issuer level.

Table 4 presents the results of the main regression. The estimated coefficients in Column (1) indicate that after price disclosure issuers monotonically increase product complexity compared to non-disclosing issuers. All dummy coefficients are individually and jointly statistically different from zero. The point estimate for the coefficient that captures the effect nine or more months after disclosure indicates an increase in the number of features by up to 0.28 relative to the control group. Compared to a standard BRC containing three features, this change corresponds to an increase in complexity of 9.3%.[11] Over a time period of nine years, Célérier and Vallée (2017) find an increase in the overall complexity of around 15%. Considering the much shorter observation period of this study and that the difference-in-differences estimate measures the change in complexity in excess of the changes in the control group, this effect is economically meaningful. In Column (2), I replace the dynamic difference-in-differences variables in Eqn. (1) with a dummy variable that is equal to one if the product is subject to price disclosure. This approach allows me to measure the average effect of the price disclosure policy. The point estimate of the included dummy variable suggests that issuers add on average 0.17 more features after price disclosure compared to the control group. Next, I test whether the parallel trends assumption holds. To this end, I add leads of the variables $Disclosure_{j,t}^{m}$ to Eqn. (1) by including dummies for whether issuer j will start disclosing in 2–4 months, 5–7 months, or 8 or more months. As shown in Column (3) of Table 4, the estimated coefficients of the lead variables are neither individually nor jointly statistically different from zero. Figure 4 displays the coefficients graphically. The timing evidence, in conjunction with the parallel trends, might speak for a causal link between price disclosure and an increase in complexity. Overall, the findings presented in Table 4 are in line with the implications of the literature on learning and obfuscation

[11] An alternative approach to interpreting this result would be to set this increase in relation to the average number of added features in excess of the standard BRC (1.21). In this case, the increase in complexity in excess of the standard product amounts to more than 23%.

(Carlin and Manso, 2010; Ellison and Ellison, 2009; Ellison and Wolitzky, 2012).

Predictions of the current literature on the impact of competition on obfuscation are divided. The models of Shapiro (1994) and Carlin and Manso (2010) predict a negative relation between obfuscation and competition, whereas several other models predict that obfuscation increases with competition (Carlin, 2009; Chioveanu and Zhou, 2013; Spiegler, 2016, 2006)). An experimental study finds no significant effect of competition on obfuscation activities (Kalaycı, 2016). The coefficient of $Competition$ is positive and significant in all regression specifications, suggesting that competition is positively correlated with complexity.

INSERT TABLE 4 NEAR HERE

INSERT FIGURE 4 NEAR HERE

Multiple recent papers on the difference-in-differences setting put particular focus on potential heteregenous treatment effects (Abraham and Sun, 2018; Callaway and Sant'Anna, 2018; de Chaisemartin and D'Haultfoeuille, 2019). de Chaisemartin and D'Haultfoeuille (2019) show that the violation of the constant treatment assumption can result in negative weights for one or some of the individual treatment effects, e.g., the treatment effect of issuers that adopted the policy in the second round. In order to test the robustness of my results with respect to heteregenous treatment effects, I calculate the weights for every $DiscloserGroup$ x $TimePeriod$ combination (non-adopters, early-adopters before and after, late-adopters before and after) in the average treatment effect based on the methodology of de Chaisemartin and D'Haultfoeuille (2019). Since all the resulting weights are positive, I conclude that the my estimated difference-in-differences coefficients are robust to heteregenous treatment effects.

One remaining empirical challenge is that unobserved time-variant characteristics are potentially correlated with both the decision to disclose and an increase in complexity. I mitigate this concern by employing a triple differences approach. To this end, I use the

German market as a control group. The German market serves as a suitable counterfactual for the Swiss market for multiple reasons. First, the issuers in both markets follow the guidelines governed by the European Structured Investment Products Associations (EUSIPA) pertaining to the standardization and classification of structured products.[12] Therefore, products issued in Switzerland and Germany are directly comparable. Second, the German market was not subject to changes in transparency during the observation period, as all products issued in Germany are already price transparent throughout the observation period. Third, while the two countries are similar in terms of the economic and cultural environment, the markets for structured products are isolated from each other. Products issued in Switzerland are subject to selling restrictions for most countries outside of Switzerland, in particular, the European Economic Area and the US. Most product term sheets contain the following or a similar paragraph:

> No action has been or will be taken to permit a public offering of the products or possession or distribution of any offering material in relation to the products in any jurisdiction, where such action for that purpose is required. Consequently, any offer, sale or delivery of the products, or distribution or publication of any offering material relating to the products, may only be made in or from any jurisdiction in compliance with applicable laws and regulations not imposing any obligations on the issuing parties or the lead manager. Possible limitations resulting from legal restrictions with regard to cross-border communication and cross-border business concerning the products and related information remain reserved. Offering and selling restrictions in particular apply with respect to the EEA, UK, Hong Kong and Singapore. The products may not be offered or sold within the United States or to, or for the account or benefit of US persons (as defined in Regulation S).

Likewise, the public offering of products issued in Germany is usually limited to

[12] See `https://eusipa.org/`.

investors located in Germany, Liechtenstein, Luxembourg, and Austria. These selling restrictions are important because they minimize the concern of spillover effects caused by price disclosure, for example, a systematic shift in the investor population due to an inflow of German investors in Switzerland. Fourth, anecdotal evidence suggests that the Swiss and German units of an issuer use a similar production technology for both markets, for example, Vontobel use the same online platform for Switzerland and Germany.[13]. If the Swiss and German units of an issuer were completely independent, the estimation of the triple differences approach would yield the same results as the difference-in-differences approach.

The data set for the German market is provided by Boerse Stuttgart and comprises all structured products listed at the German exchange for structured products between May 2014 and March 2016. The data set contains information on the product parameters, including issuance and maturity date, name of the issuer, underlying, coupon, and barrier, as well as a short description of the product. In order to create a comparable data set, I focus on BRCs of issuers that are also active on the Swiss market (and vice versa). Again, I follow the methodology described in Section 3.2 to determine the number of features embedded in a product. The final sample consists of 11'945 BRCs issued in Germany and 4'249 BRCS issued in Switzerland by seven different issuers.[14] Only one of these issuers, Vontobel, starts to disclose in Switzerland during the observation period. Therefore, this analysis consists of only one disclosure event.

Using this data, I estimate a triple differences regression model. First, I start with the simplest model specification:

[13]See `https://derinet.vontobel.com/CH/EN/Home` for the Swiss market and `https://zertifikate.vontobel.com/DE/Home` for the German market

[14]These issuers are BNP Paribas, Commerzbank, Deutsche Bank, Goldman Sachs, Société Générale, UBS, and Vontobel.

$$\begin{aligned}&Features_{i,j,c,t} = \alpha_0 + \beta_1 Vontobel_j x Swiss_c + \\ &\beta_2 Vontobel_j x Treatment_t + \beta_3 Treatment_t x Swiss_c + \\ &\beta_4 Vontobel_j x Treatment_t x Swiss_c + Controls_{i,j,c,t} + FixedEffects_{j,c,t} + \epsilon_{i,j,c,t},\end{aligned} \tag{2}$$

where $Features$ is the number of features embedded in product i based on the methodology described in Section 3.2. $Vontobel_j$ is a dummy variable that is equal to one if product i is issued by Vontobel, $Swiss_c$ is a dummy variable that is equal to one if product i is issued in Switzerland and $Treatment_t$ is a dummy variable that is equal to one if product i is issued after Vontobel starts to disclose prices. I include year-month fixed effects, issuer fixed effects, and country fixed effects in order to control for variables that are either constant across issuers, over time within issuer, and over time within country. Further, I include variables to control for a product's i's time to maturity (measured in years), underlying asset class (equity, interest rates, exchange rates, commodities, or others), and competition (measured as the number of products issued in month t by all issuers other than issuer j in country c). The main coefficient of interest is β_4 (the triple differences estimate). This coefficient measures the change in the complexity of products issued by Vontobel in Switzerland in response to price disclosure compared to the changes in the complexity of the other issuers in Switzerland and over of the changes in the complexity by Vontobel in Germany compared to the other issuers in Germany. Therefore, the model also controls for time-variant unobservable variables that are constant within Vontobel across countries. The standard errors are clustered at the country-issuer level.[15]

Table 5 presents the results. The estimates in Column (1) further confirm the findings presented in Table 4. The point estimate of β_4 indicates that after price disclosure the Swiss unit of Vontobel increased the number of features on average by 0.14 com-

[15]The main results remain significant if the standard errors are clustered at the issuer level. I cluster the standard errors at the country-issuer level because the standard errors are larger for most of the coefficients, and the significance tests thus more conservative.

pared to the other issuers in Switzerland and in excess of the changes in the number of features between the German unit of Vontobel and the other issuers in Germany. The dynamic model presented in Column (2) shows that complexity, while not monotonously, is increasing over time. In Columns (3) and (4), I include issuer-country FE in order to control for issuer-specific unobserved variables that are constant over time but different across countries. The results are robust to this specification. Finally, I add issuer-specific linear year-month time trends to the estimation model to capture issuer-specific time trends in $Features$ that are common across countries. The results presented in Columns (5) and (6) show that the magnitudes of the coefficients are higher in this specification.[16] Overall, this analysis lends further support to a causal link between price disclosure and an increase in complexity.

INSERT TABLE 5 NEAR HERE

4 Demand Estimation

In this section, I estimate the impact of complexity on price elasticity using aggregated market data. For this analysis, I focus on all products with price disclosure issued in Switzerland. BRCs provide an ideal laboratory to study the demand behavior of investors for several reasons. First, BRCs are characterized by a limited set of observable parameters, in particular, the underlying, time to maturity, product currency, barrier level, and coupon. Most of the additional features such as the *Quanto* or *Underlying Selection* feature are implicitly defined and need no further observable parameters such as a second barrier level, and thus enable a comparison among similar products without further product parameters.[17]. To this end, I use the following approach: As in Egan

[16] In unreported results, I replace the issuer time-trends with issuer-year-month fixed effects. The triple differences coefficient remains positive and significant.

[17] Only products with an *Autocall* feature (a subgroup of the *Early Redemption* feature) require an additional explicit parameter. In order to ensure a parsimonious estimation model, I exclude these products from the analysis.

(2019), I divide the products into distinct markets. I assign all products issued in the same month, on the same underlying, with the same time to maturity, and with identical features to the same market. For example, all one-year BRCs traded in CHF, issued in July 2015, linked to the performance of Bayer AG, and containing a *Quanto* feature identify one market. For the analysis, I consider only markets with at least two observations. This procedure allows me to identify products that are suitable substitutes. The final sample consists of 392 distinct markets with 948 BRCs.

Second, the issue price and parameters of a product are set in advance, and all demand is satisfied (Egan, 2019). In many markets, the direct endogenous relation between price and supply is a major empirical concern. This particular setting of the market for structured products, however, helps me to overcome this endogeneity challenge because prices are determined before demand, and supply is completely elastic.

Using the described data, I estimate the following demand model:

$$\begin{aligned}
&ln(Volume)_{i,j,u,t} = \alpha_0 + \beta_1 ln(1+TER_i) + \beta_2 Features_i + \\
&\beta_3 ln(1+TER_i) x Features_i + \beta_4 ln(1+TER_i)^{Market} + OwnProductParameter_i + \\
&MarketProductParameter_i + Controls_{i,j,u,t} + \\
&FixedEffects_{j,u,t} + \epsilon_{i,j,u,t},
\end{aligned} \tag{3}$$

where $Volume$ is a product's issuance volume (measured in CHF), TER is the total expense ratio of product i disclosed by issuer j, and $Features$ is the number of features embedded in product i based on the methodology described in Section 3.2. $OwnProductParameter$ is a vector of variables that capture product i's observable parameters, in particular a product's annualized coupon, barrier (measured in % of the underlying reference price), and time to maturity (measured in years). In the base regression, I include year-month fixed effects, issuer fixed effects, and underlying fixed effects. Underlying fixed effects also measure whether a product is issued on one or multiple underlyings, and thus implicitly captures the *UnderlyingSelection* feature. To avoid any mechanical effect, I therefore exclude the *Underlying Selection* feature and adjust the complexity measure downwards. While simultaneously controlling for all other observable parameters of product i, TER measures the direct impact of price on demand.

In order to proxy for the price of the substitute good, I include the average TER of all other products in the same market as product i (TER^{Market}). $MarketProductParameter$ is a vector of variables that capture the parameters of the other products in the same market as product i, in particular, the average annualized coupon and average barrier (measured in % of the underlying reference price). Further, I include a control variable for competition measured as the number of products issued in month t by all issuers other than issuer j. The standard errors are clustered at the issuer-level.

In a correctly specified model, demand is expected to decrease with the price of product i and to increase with the price of its substitutes. The main coefficient of interest is β_3. If complexity is associated with lower price sensitivity, β_3 should be positive and statistically significant (Chioveanu and Zhou, 2013; Piccione and Spiegler, 2012; Wilson, 2010).[18]

The results of the demand estimation are presented in Table 6. As a plausibility check, I first estimate the own-price price elasticity and the cross-price price elasticity of demand. To this end, I estimate Eqn. (3) but exclude the interaction term between TER and $Features$. As shown in Column (1), the own-price elasticity is around -2.26 and the cross-price elasticity is around 1.47. Both coefficients have the expected sign, a plausible magnitude, and are statistically significant. Column (2) presents the estimates of Eqn. (3). In line with the predictions, the coefficient of the interaction term is positive and significant. This finding supports the theory that complexity acts as an obfuscation mechanism to reduce price sensitivity. The magnitude is also economically significant. As shown in Table 4, issuers with price disclosure increase the number of features by 0.13 in

[18] Here, I assume a linear relation between complexity and price sensitivity. The results are also robust if I also include the quadratic term of $Features$ and its interaction with TER.

the short term and by 0.28 features in the long term. Therefore, adding 0.13 features to a standard BRC reduces the own-price sensitivity by around 15% (0.13 * 6.23 / (-23.96 + 3*6.23)), whereas adding 0.28 features reduces the own-price sensitivity by around 33% (0.28 * 6.23 / (-23.96 + 3*6.23)).

INSERT TABLE 6 NEAR HERE

Next, I include market fixed effects based on the definition of markets as described above. Comparing products within markets allows me to implicitly control for the effect of factors that are common to all products within the same market, mitigating the concern that the results are driven by demand for unobserved product characteristics, for example, a high demand for a currency-hedged product on a particular underlying in a particular month or a high demand for one particular combination of features. As shown in Column (3), the results remain statistically significant but are economically smaller yet still meaningful. Based on the results, the estimated effect for a standard BRC amounts to a reduction in price sensitivity of approximately 9% (0.13 * 6.85 / (-30.20 + 3*6.85)) in the short term and approximately 20% (0.28 * 6.85 / (-30.20 + 3*6.85)) in the long term.

5 Alternative Explanations

In the following, I discuss alternative explanations for the findings presented in Section 4. Egan (2019) analyzes the role of brokers in the market for structured products in the US and finds that distribution fees are a significant determinant of issuance volume because brokers are more incentivized to sell products with higher distribution fees. Therefore, an alternative explanation of the result is that more complex products are potentially associated with higher distribution fees, and are thus stronger advertised by brokers. I show that this alternative explanation does not drive the results by first providing an intuitive explanation and then by testing it empirically: Unlike the market in the US, most of the structured products in Europe are directly distributed by the issuer. A survey conducted among 6'000 investors across eight EU member states shows that 85% of the investors purchase their structured products directly from the investment provider (Chater et al., 2010). The answers to this survey highlight the stark contrast to the US market, where all structured products are distributed through brokers (Egan, 2019). Therefore, the role of the brokers in the distribution of the products should be of less concern in Europe. In order to statistically test the alternative explanation, I split TER into its two components - the distribution fees (DF) and the remaining costs (TER *minus* DF), and repeat the estimations of Columns (2) and (3). As shown in Columns (4) and (5), the single and the interaction term containing DF are not significant whereas the impact of complexity on price sensitivity is significant for the remaining part of the costs. This finding suggests that the lower price sensitivity for more complex products is not driven by stronger incentives for brokers to sell the products but is directly related to the price of a product.

The following two alternative explanations build on the notion that price disclosure caused a change in the investor population of transparent issuers. A potential shift in the investor population is a valid concern because the empirical setting only allows me to estimate the price elasticity for products subject to price disclosure. As a consequence, the investors in this sample are potentially not representative of the whole market. A change in the investor population does not necessarily contradict the finding that complexity lowers price sensitivity but could influence the magnitude of the effect.

One of the potential explanations for a shift in the investor population is that price disclosure lowers search costs, and therefore attracts new investors with search costs that are otherwise too high to make their market participation worthwhile. These new investors potentially exhibit lower financial literacy and are thus less price sensitive. This explanation is closely related to the model of Moraga-González et al. (2017) that incorporates the impact of changes in search cost on the decision to participate (extensive margin). Similarly, Abel (2001) assumes that participation in the financial markets is subject to fixed costs that are too high for investors with lower income and, as shown by Calvet et al. (2009), potentially lower financial sophistication. In the context of this model, price disclosure could lower the costs to participate for all investors, and thus increases the existing investor population through an inflow of investors with lower financial sophistication. As a result, the average issuance volume of an issuer should increase after price disclosure. An increase in investor population through an inflow of additional investors, however, is only driving the presented results if the inflow of investors with potentially lower financial sophistication is systematically more pronounced in markets with higher complexity, for example, if after price disclosure a disproportionately larger share of financially less literate investors starts to invest in more complex BRCs. This assumption seems counterintuitive because investing in more complex products potentially requires higher search efforts (Chioveanu and Zhou, 2013; Piccione and Spiegler, 2012; Wilson, 2010). Therefore, it is a priori unclear why more investors with relatively high search costs would choose to participate in particularly complex markets. Testing this theory is challenging because a precise analysis requires transaction data on the investor level and a proxy for individual financial literacy. The empirical setting allows me only to test this theory on an aggregated level. To this end, I employ the difference-in-differences setting presented in Section 3.3 but use issuance volume as the dependent variable. Table 7 shows the results. The findings presented Columns (1) and (2) indicate that there is no significant change in issuance volume due to price disclosure. If anything, the negative sign of the estimated coefficient suggests a decrease in issuance volume. In Column (3), I include the interaction term between complexity and a dummy that is equal to one if product i is subject to price disclosure. This term measures the impact of price disclosure with respect to the level of complexity. The negative and significant coefficient indicates that the decrease in issuance volume is more pronounced for more complex products. Even though the analysis is conducted only at the aggregated market level, the findings tend to contradict the theory that price disclosure attracts new investors because the demand for more complex products decreases more after price disclosure.

INSERT TABLE 7 NEAR HERE

Another potential explanation for the shift in the investor population is adverse selection (Christoffersen and Musto, 2002; Ellison, 2005; Gabaix and Laibson, 2006). Price disclosure could reveal to investors that the average price of structured products is higher than expected and that the ex-post performance after fees is often negative (Henderson and Pearson, 2011; Vokata, 2018). This, in turn, could drive more sophisticated investors out of the market or to issuers without price disclosure, resulting in a, on average, less sophisticated investor population for transparent issuers (Gabaix and Laibson, 2006). This explanation is consistent with the findings of the demand estimation if the average investor sophistication decreases more for more complex products after price disclosure. As shown by Célérier and Vallée (2017), the number of features is positively correlated with higher hidden markups. Therefore price disclosure could have a stronger adverse selection effect for more complex products because financially sophisticated investors realize that more complex products are relatively more expensive. In order to proxy for investor sophistication, I calculate the average trading size of a product on the secondary market. This measure for financial sophistication is motivated by the literature that shows a positive relation between trading size and financial sophistication (Bhattacharya, 2001; Battalio and Mendenhall, 2005; Bhattacharya et al., 2007; Easley and O'Hara, 1987). I repeat the difference-in-differences setting presented in Section 3.3 but use the average trading size as the dependent variable.[19] The results are presented in Columns (4) and (5) of Table 7. In Column (4), I estimate the average effect of price disclosure on the measure for financial sophistication. The findings suggest no significant effect on the average trading size. In Column (5), I include the interaction with $Features$. Even though not statistically significant, the negative coefficient of the interaction term suggests that the

[19] I exclude the 2'808 products without trading volume on the secondary market from the analysis.

adverse effect of price disclosure on investor sophistication is stronger for more complex products. Therefore, the adverse selection explanation can not be completely ruled out and might influence the magnitude of the effect of complexity on price sensitivity.

6 Conclusion

In this study, I analyze how issuers of retail structured products respond to a price transparency policy. Using a simple measure for product complexity, I show that issuers started to steadily increase the level of complexity of their products once they commit to price disclosure. Already within two months after an issuer starts to disclose, the average number of features embedded in their products increases significantly compared to products of issuers without price disclosure. Moreover, the results suggest that product complexity is higher when markets are more competitive. Next, I examine the effect of complexity on the price sensitivity of investors. To this end, I estimate a demand model that captures virtually all of the observed and unobserved product characteristics. I show that complexity significantly reduces the price sensitivity of the investors. This finding raises the concern that an increase in complexity causes more inefficient allocations. Since households in Switzerland exhibit a comparatively high level of financial sophistication, the results of this study most likely provide a lower bound to the adverse effects of complexity (Brown and Graf, 2013).

Overall, the findings of this study are consistent with the model of Carlin and Manso (2010) predicting that financial institutions engage in wasteful obfuscation activities when learning by investors is facilitated.

A sound understanding of the interaction between obfuscation and learning in the financial markets can guide policymakers in designing the appropriate policy to protect investors. This study provides empirical evidence that advances such as price disclosure or educational initiatives can induce unexpected social welfare costs. Besides, the results suggest that investors can not rely on traditional market mechanisms such as competition between financial institutions to reduce obfuscation in the financial system. The empirical analysis of the impact of alternative types of policy, such as product standardization provides an interesting field for further research (Miao, 2010).

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Table 1
Overview of the Sample

This table presents an overview of the product characteristics in the sample. The dataset consists of retail barrier reverse convertibles (BRC) issued in Switzerland between May 2014 and March 2016. Each panel reports the three most common characteristics grouped by issuer, time to maturity, product currency, underlying asset class, and underlying. The numbers in parantheses correspond to the relative frequency with respect to the full sample.

	Number of Products (%)
Panel A: By Issuer	
Vontobel	3’375 (27.3%)
Leonteq	1’884 (15.3%)
Julius Baer	1’636 (13.3%)
Panel B: By Time to Maturity	
1 Year	7’117 (57.7%)
1.5 Years	1’725 (14.0%)
2 Years	1’489 (12.1%)
Panel C: By Product Currency	
CHF	7’356 (59.6%)
EUR	2’663 (21.6%)
USD	2’196 (17.8%)
Panel D: By Underlying Asset Class	
Equity	12’146 (98.4%)
Commodity	169 (1.4%)
Others	23 (0.2%)
Panel E: By Underlying	
Euro Stoxx 50 / S&P 500 / SMI	1’489 (12.1%)
Nestlé / Novartis / Roche	786 (9.4%)
Euro Stoxx 50 / Nikkei 225 / S&P 500 / SMI	380 (4.5%)

Table 2

Descriptive Statistics

This table presents the descriptive statistics of the sample used in this study. The dataset consists of retail barrier reverse convertibles (BRC) issued in Switzerland between May 2014 and March 2016. $IssuanceVolume$ is the issue volume of a product in CHF and $Time\ to\ Maturity$ is defined as the difference between the issuance data and maturity date, measured in years. $Competition$ is defined as the number of products issued in the same month by all competing issuers. $Features$ is the number of features embedded in a product based on the methodology described in Section 3.2. TER (DF) is the total expense ratio (distribution fee) disclosed by the issuer of a product before issuance. $Barrier$ is a product's barrier level, measured as percentage of the reference underlying price and $Coupon$ is the annualized coupon of a product.

	N	Mean	Std. Dev.	Q25	Median	Q75
Issuance Volume (in mn CHF)	12'341	15.29	11.65	5.00	10.00	28.33
Time to Maturity (in years)	12'341	1.39	0.69	1.00	1.06	1.50
Competition	12'341	462.23	84.34	417	462	501
Features	12'341	4.21	1.00	3.00	4.00	5.00
TER (in %)	5'724	1.68	0.63	1.37	1.65	1.93
DF (in %)	5'724	0.66	0.33	0.50	0.69	0.75
Barrier (in %)	5'724	66.91	9.27	60.00	69.00	75.00
Coupon (in %)	5'724	7.45	3.10	5.42	6.78	8.80

Table 3

Features

This table presents an overview of all features and their rate occurence in the sample. Features #1 to #8 are based on the defintion of Célérier and Vallée (2017). Features #9 and #10 are described in Section 3.2. Column (1) presents the number of products with the corresponding feature for the whole samples, whereas Column (2) and Column (3) present the statistics for the sample of products without price disclosure and with price disclosure, respectively. The number in brackets refer to the relative frequency of the feature with respect to the corresponding sample.

#	Feature	Number of Products (all)	Number of Products (non-disclosed)	Number of Products (disclosed)
1	Primary Feature	12'341 (100%)	6'617 (100%)	5'724 (100%)
2	Initial Subsidy	0 (0%)	0 (0%)	0 (0%)
3	Underlying Selection	8'366 (67.79%)	4'388 (66.31%)	3'978 (69.50%)
4	Increased Downside	12'341 (100%)	6'617 (100%)	5'724 (100%)
5	Limited Upside	0 (0%)	0 (0%)	0 (0%)
6	Path Dependence	29 (0.23%)	27 (0.00%)	2 (0.00%)
7	Exotic Condition	12'150 (98.45%)	6'512 (98.41%)	5'638 (98.50%)
8	Early Redemption	4'360 (35.33%)	2'320 (35.06%)	2'040 (35.64%)
9	Quanto	2'244 (18.18%)	1'015 (15.34%)	1'229 (21.47%)
10	Collateral Secured	193 (1.56%)	32 (0.01%)	161 (2.81%)

Table 4
Effects of Disclosure on Complexity (Difference-in-Differences)

This table presents the regression estimates using a dynamic difference-in-differences approach on the sample of retail barrier reverse convertibles (BRC) issued in Switzerland between May 2014 and March 2016. The regression in Column (1) is estimated with the model defined in Eqn. (1). In Column (2), I replace the dynamic difference-in-differences variables in Eqn. (1) with a dummy variable that is equal to one if the product is subject to price disclosure. In Column (3), I extend Eqn. (1) with a series of dummy variables that are equal to one if the issuer will start disclosing in m months. The dependent variable is *Features*, which is the number of features embedded in a structured product based on the methodology described in Section 3.2. *Time To Maturity* is defined as a product's maturity measured in years, *Volume* as a product's issuance volume measured in CHF, and *Competition* as the number of products issued in month t by all issuers other than issuer j. I include year-month FE, issuer FE, and underlying asset class FE. The standard errors are clustered at the issuer-level. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) Features	(2) Features	(3) Features
0 – 2 months later	0.130*		0.103
	(1.87)		(1.46)
3 – 5 months later	0.163***		0.141***
	(2.71)		(3.27)
6 – 8 months later	0.194**		0.169**
	(2.28)		(2.10)
$\geq$ 9 months later	0.279***		0.257***
	(3.60)		(3.26)
Average Effect		0.172***	
		(3.17)	
2 – 4 months before			-0.020
			(-0.26)
5 – 7 months before			-0.051
			(-0.48)
$\geq$ 8 months before			-0.016
			(-0.11)
Time To Maturity	0.381***	0.382***	0.382***
	(4.46)	(4.49)	(4.45)
ln(Volume)	0.183	0.164	0.184
	(1.27)	(1.08)	(1.28)
Competition	0.005***	0.005***	0.004***
	(2.75)	(2.88)	(2.63)
F-Test Joint Significance (later)	p = 0.04		p = 0.03
F-Test Joint Significance (before)			p = 0.93
Year-Month FE	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes
Underlying Asset Class FE	Yes	Yes	Yes
Observations	12'341	12'341	12'341
R-squared	0.427	0.427	0.427

Table 5
Effects of Disclosure on Complexity (Triple Differences)

This table presents the regression estimates using a difference-in-differences-in-differences approach on the sample of retail barrier reverse convertibles (BRC) issued in Switzerland and Germany between May 2014 and March 2016. The regression in Column (1) is estimated with the model defined in Eqn. (2). In Columns (2), (4), and (6), I replace the triple differences coefficient of Eqn. (2) with a series of dummy variables that are equal to one if the unit of Vontobel in Switzerland will start disclosing in m months. The dependent variable is $Features$, which is the number of features embedded in a structured product based on the methodology described in Section 3.2. $Vontobel$ is a dummy variable that is equal to one if the product is issued by Vontobel, $Swiss$ is a dummy variable that is equal to one if the product is issued in Switzerland, and $Treatment$ is a dummy variable that is equal to one if the product is issued in or after October 2014. $Time\ To\ Maturity$ is defined as a product's maturity measured in years and $Competition$ as the number of products issued in the same month and in the same country by all other issuers. I include year-month FE, issuer FE, country FE, and underlying asset class FE. Depending on the specification, I also include issuer-country FE and issuer-time trends. The standard errors are clustered at the country-issuer level. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) Features	(2) Features	(3) Features	(4) Features	(5) Features	(6) Features
Vontobel x Swiss	-0.657***	-0.706***				
	(-10.69)	(-18.13)				
Vontobel x Treatment	-0.096***	-0.070**	-0.024	-0.226**	-0.161*	0.000
	(-3.06)	(-2.36)	(-0.43)	(-2.31)	(-1.77)	(0.02)
Treatment x Swiss	-0.019	-0.009	-0.024	-0.014	-0.129	-0.136
	(-0.32)	(-0.15)	(-0.43)	(-0.24)	(-0.78)	(-0.87)
Swiss x Vontobel x Treatment	0.144**		0.147***		0.275*	
	(2.51)		(2.71)		(1.85)	
0 – 2 months later		-0.086		-0.082		-0.028
		(-0.99)		(-0.98)		(-0.18)
3 – 5 months later		0.130*		0.127*		0.216
		(1.87)		(1.87)		(1.39)
6 – 8 months later		0.103***		0.105***		0.218*
		(4.05)		(4.05)		(1.85)
$\geq$ 9 months later		0.208***		0.212***		0.337**
		(3.42)		(3.66)		(2.10)
Time To Maturity	0.207	0.212	0.208	0.212	0.212	0.212
	(1.49)	(1.49)	(1.50)	(1.49)	(1.50)	(1.49)
Competition	0.000	0.000	0.000	0.000	0.000	-0.000
	(0.84)	(0.09)	(0.97)	(0.21)	(0.77)	(-0.54)
F-Test Joint Signifiance (later)		p = 0.00		p = 0.00		p = 0.00
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Issuer-Country FE	No	No	Yes	Yes	Yes	Yes
Issuer-Year-Month FE	No	No	No	Yes	No	No
Issuer Time Trends	No	No	No	No	Yes	Yes
Underlying Asset Class FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16'194	16'194	16'194	16'194	16'194	16'194
R-squared	0.205	0.211	0.208	0.214	0.211	0.216

Table 6
Demand Estimation

This table presents the regression estimates using Eqn. (3) on the sample of retail barrier reverse convertibles (BRC) issued in Switzerland that are subject to price disclosure. The dependent variable is $Volume$, which is the product's issuance volume in CHF. TER is the product's total expense ratio disclosed by the issuer, $Features$ is defined as the number of features embedded in a structured product based on the methodology described in Section 3.2, DF is the product's distribution fee disclosed by the issuer, and $TER\ minus\ DF$ is calculated as the difference between TER and DF. $Barrier$ is the the product's barrier level measured in percentage of the underlying reference price and $Coupon$ is the product's annualized coupon measured in percentage. $Barrier^{Market}$ is the average barrier level and $Coupon^{Market}$ is the average annualized coupon of all other products in the same market as the product, respectively. $Time\ to\ Maturity$ is defined as a product's maturity measured in years and $Competition$ as the number of products issued in the same month by all other issuers. I include Year-Month FE, Issuer FE, and Underlying FE. Depending on the specification, I also include Market FE. The standard errors are clustered at the issuer-level. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) ln(Volume)	(2) ln(Volume)	(3) ln(Volume)	(4) ln(Volume)	(5) ln(Volume)
ln(1+TER)	-2.258***	-23.964**	-30.199*		
	(-4.11)	(-2.42)	(-1.73)		
ln(1+TER) x Features		6.230**	6.847**		
		(2.13)	(2.04)		
ln(1+ DF)				-12.191	-17.712
				(-0.46)	(-0.75)
ln(1 + DF) x Features				1.967	2.837
				(0.30)	(0.72)
ln(1+ TER minus DF)				-26.211***	-32.617**
				(-4.01)	(-2.17)
ln(1 + TER minus DF) x Features				7.173***	7.629***
				(3.39)	(2.61)
$ln(1+TER)^{Market}$	1.472**	0.867	-4.241	1.201	-4.379
	(2.04)	(0.78)	(-0.57)	(1.30)	(-0.58)
Barrier	-0.092	-0.127	0.410	-0.101	0.408
	(-0.61)	(-0.72)	(0.38)	(-0.57)	(0.38)
Coupon	-0.104	-0.153	-0.667	-0.123	-0.612
	(-0.21)	(-0.30)	(-0.26)	(-0.36)	(-0.23)
$Barrier^{Market}$	0.121	0.080	0.736	0.085	0.746
	(1.57)	(0.93)	(0.47)	(0.89)	(0.50)
$Coupon^{Market}$	-0.421	-0.452	-1.001	-0.475	-1.022
	(-0.99)	(-0.99)	(-0.29)	(-1.01)	(-0.30)
Competition	0.001**	0.001**	0.001	0.001**	0.001
	(2.35)	(2.16)	(1.53)	(2.30)	(1.54)
Features	0.092	-0.007		0.015	
	(1.23)	(-0.26)		(0.51)	
Time to Maturity	-0.034	-0.041*		-0.057**	
	(-1.50)	(-1.93)		(-2.45)	
Year-Month FE	Yes	Yes	No	Yes	No
Issuer FE	Yes	Yes	Yes	Yes	Yes
Underlying FE	Yes	Yes	No	Yes	No
Market FE	No	No	Yes	No	Yes
Observations	948	948	948	948	948
R-squared	0.969	0.969	0.979	0.969	0.979

Table 7
Effects of Disclosure on Issuance Volume (Difference-in-Differences)

This table presents the regressions using a dynamic difference-in-differences approach on the sample of retail barrier reverse convertibles (BRC) issued in Switzerland between May 2014 and March 2016. The regression model in Column (1) (Column (2)) corresponds to Column (2) (Column (1)) of Table 4). In Columns (1) to (3), the dependent variable is $Volume$, which is a product's issuance volume measured in CHF. In Columns (4) and (5), the dependent variable is $Trading\ Size$, which is calculated as the ratio between the cumulated trading volume on the secondary market divided by the number of transactions on the secondary market. $Features$ is defined as the number of features embedded in a structured product based on the methodology described in Section 3.2. $Time\ To\ Maturity$ is a product's maturity measured in years, and $Competition$ as the number of products issued in month t by all issuers other than issuer j. I include year-month FE, issuer FE, and underlying asset class FE. The standard errors are clustered at the issuer-level. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) ln(Volume)	(2) ln(Volume)	(3) ln(Volume)	(4) ln(Trading Size)	(5) ln(Trading Size)
0 – 2 months later	-0.085				
	(-1.17)				
3 – 5 months later	-0.222				
	(-1.25)				
6 – 8 months later	-0.329				
	(-1.42)				
$\geq$ 9 months later	-0.616				
	(-1.40)				
Average Effect		-0.261	0.064	0.085	0.380
		(-1.37)	(0.25)	(1.18)	(1.51)
Average Effect x Features			-0.074*		-0.067
			(-1.85)		(-1.41)
Features	0.043	0.042	0.075	0.046	0.077*
	(1.34)	(1.22)	(1.64)	(1.00)	(1.65)
Time To Maturity	0.036	0.037	0.040	0.022	0.024
	(1.29)	(1.53)	(1.64)	(0.56)	(0.61)
Competition	0.000	-0.001	-0.001	-0.001	-0.001
	(0.27)	(-0.63)	(-0.42)	(-1.51)	(-1.27)
ln(Volume)				0.030	0.024
				(1.03)	(0.96)
F-Test Joint Significance (later)	p = 0.46				
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes	Yes	Yes
Underlying Asset Class FE	Yes	Yes	Yes	Yes	Yes
Observations	12'341	12'341	12'341	9'533	9'533
R-squared	0.873	0.864	0.865	0.038	0.039

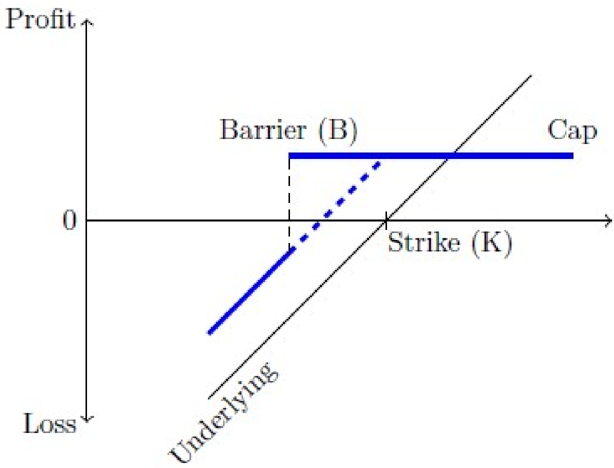

Figure 1
Payoff Profile: Barrier Reverse Convertible

This figure displays the payoff profile of a standard barrier reverse convertible (BRC). The value on the y-axis refer to the final payoff at the product's maturity date in the currency of the product. The values on the x-axis refers to the price of the underlying. Investors of a standard BRC give up the upside participation in the underlying in exchange for unconditional coupon payments. BRCs exhibit conditional capital protection that is active as long as the underlying never breaches the pre-specified barrier level. If the barrier level is breached during the lifetime of the product, the investor fully participates in the downside movements of the underlying. (Source figure: Kuklinski et al. (2016))

Product 1

EFG International

Termsheet as of 14/12/2015

Public Offering: CH
Yield-Enhancement Products
SSPA Product Type: 1230

8.32% p.a. Barrier Reverse Convertible on Credit Suisse

Continuous Barrier Observation

Final Fixing Date 14/12/2016; issued in CHF; listed on SIX Swiss Exchange AG

ISIN CH0304977405 - Swiss Security Number 30497740 - SIX Symbol EFGHKQ

Product 2

NOTENSTEIN
LA ROCHE
PRIVATE BANK

Termsheet as of 18/01/2016

Public Offering: CH
Yield-Enhancement Products
SSPA Product Type: 1230
Swiss Withholding Tax

5.00% p.a. Multi Barrier Reverse Convertible on EURO STOXX 50® Price Index, S&P 500®, Swiss Market Index®

Continuous Multi Barrier Observation - Autocallable - Quanto CHF

Final Fixing Date 15/01/2019; issued in CHF; listed on SIX Swiss Exchange AG

ISIN CH0304631804 - Swiss Security Number 30463180 - SIX Symbol NPAFLW

Figure 2
Complexity: Term Sheets

This figure displays excerpts of two different product term sheets. Product 1 represents a standard barrier reverse convertible (BRC), whereas Product 2 examplifies a more complex product, containing three additional features.

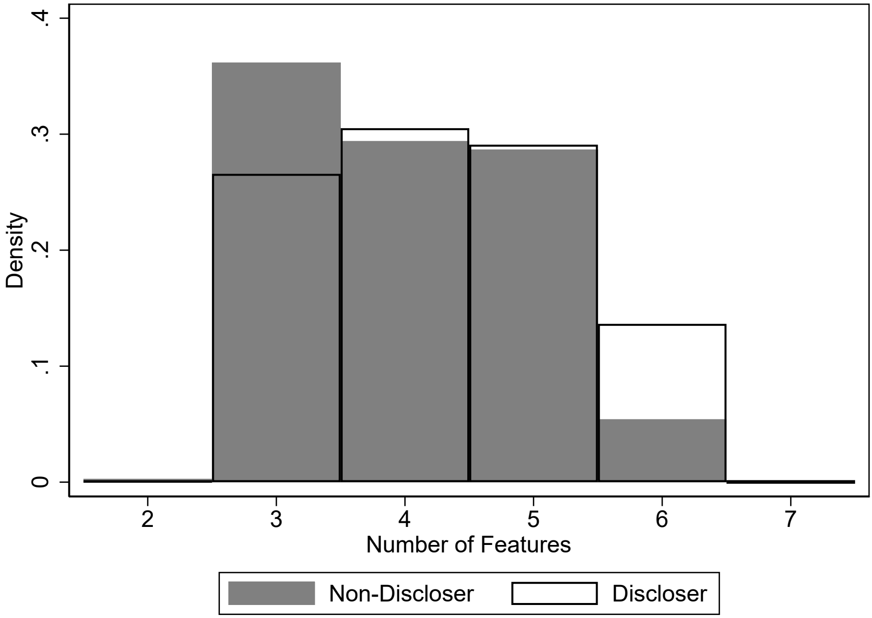

Figure 3
Histogram: Number of Features

This figure displays the distribution of product complexity of issuers that are not subject to price transparency ($Non - Discloser$) and issuers that start to disclose product prices during the sample period ($Discloser$). The values on the x-axis refers to the number of features embedded in a structured product based on the methodology described in Section 3.2.

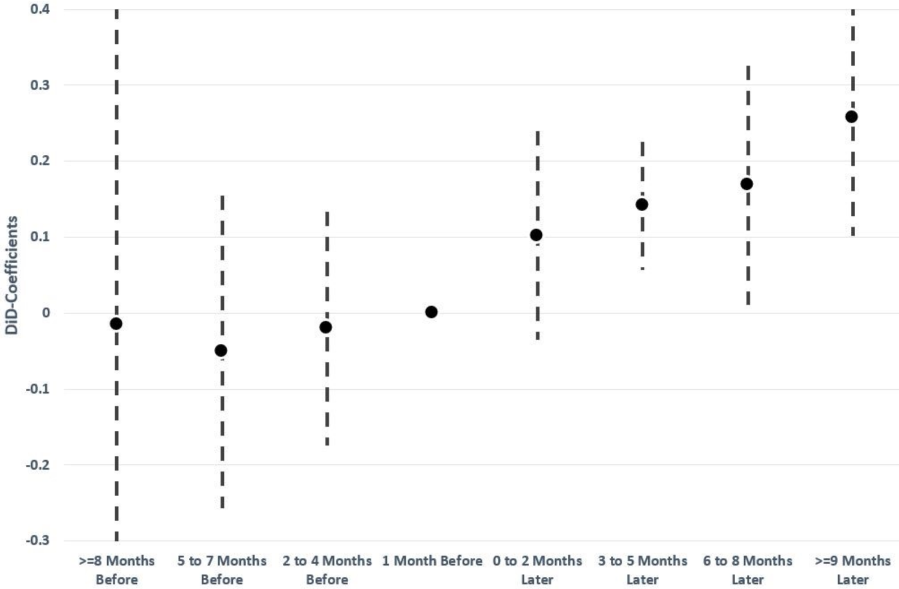

Figure 4
Difference-in-Differences: Parallel Trends Assumption

This figure shows the estimated coefficients based on the regression model presented in Column (3) of Table 5. The values on the y-axis refer to the variable *Features*, which is the number of features embedded in a structured product based on the methodology described in Section 3.2. The values on the x-axis refer to the number of months around the disclosure date. The dashed lines represent the 95% confidence interval using standard errors clustered at the issuer level.

On the Redundancy of the Value Factor

Manuel Ammann[*], Tobias Hemauer[†], and Simon Straumann[‡]

Abstract

In this paper, we propose an explanation for the empirically documented relation between the value factor and the investment factor of the Fama-French five-factor model. In particular, we argue that investors observing that a firm decreases its investment perceive the firm as riskier, and therefore adjust their valuations of the firm downwards. As a consequence, the firm's book-to-market ratio increases. In support of this conjecture, we find considerable overlap between the factor-mimicking portfolios of the value and the investment factor. We present evidence that this overlap is driven by stocks that experience an increase in their book-to-market ratios due to a decrease in their market values. Moreover, our results show that these stocks behave like low investment stocks and therefore also earn a premium. Together with actual low investment stocks, these stocks are primarily responsible for the value premium.

JEL-Code: G12

Keywords: Asset pricing model, Factor model, Value, Investment

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1 Introduction

Following its establishment, the three-factor model of Fama and French (1993, 1996) has been the dominant empirical asset pricing model in the finance literature for decades. Apart from the market factor of the CAPM, it contains a size factor and a value factor aiming to capture the empirically documented outperformance of stocks of small firms over stocks of big firms (e.g. Banz (1981)) and of stocks of firms with high book-to-market ratios over stocks of firms with low book-to-market ratios (e.g. Rosenberg et al. (1985)).

Recently there have been several propositions for new and extended empirical multifactor models. In particular, Fama and French (2015) introduce a five-factor model that extends their three-factor model with a profitability factor and an investment factor. These two factors aim to capture the empirical finding that stocks of firms with high profitability outperform stocks of firms with low profitability (e.g. Novy-Marx (2013)), and that stocks of firms with low investment outperform stocks of firms with high investment (e.g. Titman et al. (2004)). Fama and French use the standard dividend-discount model to motivate the value factor, the profitability factor, and the investment factor in their five-factor model. In particular, based on a manipulation of the standard dividend-discount formula, Fama and French draw the inference that, all else equal, firms with high book-to-market ratios, firms with low investment, and firms with high profitability should exhibit higher discount rates. In equilibrium and under market efficiency, the higher discount rates imply higher systematic risk and higher expected stock returns for high book-to-market firms, for high profitability firms, and for low investment firms.

The value factor was long considered to be the primary source of the three-factor model's explanatory power for the cross-section of stock returns. However, in the presence of the profitability factor and the investment factor, Fama and French (2015) find that the value factor hardly contributes to the explanation of stock returns. The results from a regression of the value factor on the remaining factors reveal that the value premium is primarily captured by its exposure to the investment factor. This finding suggests that the value factor's explanatory power is primarily subsumed by the investment factor. Despite this result, Fama and French keep the value factor in their five-factor model, and they as well as other researchers still employ the five-factor model that includes the value factor in subsequent work (e.g. Fama and French (2018)).

Another recently proposed factor model that has received much attention (e.g. Barillas and Shanken (2018)) is the q-factor model of Hou et al. (2015). This model consists of the market factor, a size factor, a profitability factor, and an investment factor. Hou et al. motivate the factors in their model based on investment-based asset pricing. Specifically, based on a simple economic model inspired by the q-theory and the production-based asset pricing model of Cochrane (1991), they establish a theoretical relation of profitability and investment with discount rates: for a given level of profitability, high investment firms should have lower discount rates than low investment firms, and for a given level of investment, firms with higher expected profitability should have higher discount rates than firms with lower expected profitability. This theoretical result again implies that low investment firms and high profitability firms should be subject to higher systematic risk and should thus have higher expected stock returns.

Both models agree that the discount rates and therefore the risk and expected stock returns should be higher for low investment firms and for high profitability firms. Importantly, Fama and French (2015) as well as Hou et al. (2015) offer also theoretical explanations rather than only empirical evidence, making their conclusions much more reliable. The major difference between the two models is that Hou et al. do not include a value factor due to a lack of economic motivation based on their theoretical framework.

Furthermore, Hou et al. (2015) find that their investment factor has a correlation of 0.69 with the value factor of Fama and French and that their model produces a small and insignificant intercept for the value factor. Based on these findings, Hou et al. suggest that the value factor is a noisy version of their investment factor. However, they neither verify this conjecture nor explore potential explanations for the strong empirical relation between the value factor and the investment factor.

Consequently, there is currently much controversy surrounding the value factor. On the one hand, the value factor has long been regarded as the major source of explanatory power for the cross-section of stock returns. Moreover, the value premium is a robust empirical finding, and a theoretical motivation for the value factor is provided by the dividend-discount model. On the other hand, the value factor loses its explanatory power for the cross-section of stock returns when the profitability factor and the investment factor are included. Also, the economic model of Hou et al. (2015) is unable to motivate the existence of the value factor. Consequently, the theoretical motivation as well as the practical usefulness of the value factor are called into question.

In this work, we contribute to the ongoing discussion in the literature by shedding light on the nature of the strong relationship between the value factor and the investment factor, which has been the primary source for the recent controversy surrounding the value factor. For this purpose, we introduce and test a theory that offers an intuitive explanation for the relationship between the value factor and the investment factor. In particular, our theory suggests that the close relationship is driven by a considerable overlap between their factor-mimicking portfolios. Moreover, we propose and test a particular channel of how this overlap comes into existence.

Fama and French (2015) as well as Hou et al. (2015) argue that firms with lower investment exhibit higher discount rates. Hence, a rational market participant who learns that a firm decreases its investment should increase the discount rate he/she applies to the firm's future cash flows. Therefore, market participants , all else equal, decrease the fair values assigned to the firm's stock, implying that - under some degree of semi-strong market efficiency - the firm's market value decreases. Moreover, under the assumption that the firm remains riskier, and thus that its investment remains systematically lower for some time, the decrease in the firm's market value is expected to be larger than the decrease in the firm's book value. This is because the book value decreases due to the ongoing lower investment only gradually, whereas the market value is expected to adjust immediately because the market participants start to discount all future cash flows at a higher rate as soon as they learn about the firm's change in investment. Since the market value decreases more than the book value, the firm's book-to-market ratio increases. Likewise, an increase in investment should go hand in hand with a decrease in the book-to-market ratio. If our theory holds, we expect a considerable overlap between firms with high book-to-market ratios and firms with low investment. Similarly, there should be a considerable overlap between firms with low book-to-market ratio and firms with high investment. These overlaps imply a positive association between the factor-mimicking portfolios of the value and the investment factor.[1]

This conclusion builds on the notion that changes in the firms' book-to-market ratios and investments are simultaneously reflected in the factor-mimicking portfolios of the value and investment factor. However, since the portfolios are rebalanced only once per year at the end of June based on the financial statements of the prior year, this is not necessarily the case because sophisticated market participants such as analysts and institutional investors might learn about the change in the firm's investment behavior before the change in investment is reflected in the financial statements. Therefore, the change in the book-to-market ratio might be observed before the change in investment, and is thus taken into account earlier for the portfolio formation. Hence, we expect that the factor-mimicking portfolio of the value factor not only exhibits a considerable overlap with the contemporaneous but also with the one-year ahead factor-mimicking portfolio of the investment factor.

[1]Note that the value factor goes long a diversified portfolio of stocks of high book-to-market firms (hf. value stocks) and goes short a diversified portfolio of stocks of low book-to-market firms (hf. growth stocks), both of which are rebalanced at the end of each June. Thereby, the book-to-market ratio is based on data from the fiscal year ending in the prior year (for most firms, the fiscal year ends at the end of December). Likewise, the investment factor goes long a diversified portfolio of stocks of low investment firms (hf. conservative stocks) and goes short a diversified portfolio of stocks of high investment firms (hf. aggressive stocks), both of which are rebalanced at the end of each June. Thereby, investment is measured as the asset growth from the fiscal year ending two years ago to the fiscal year ending in the prior year.

Based on our theory and the proposed channel, we derive the following two hypotheses:

> Hypothesis 1a: The factor-mimicking portfolio of the value factor has considerable overlap with the contemporaneous and the one-year ahead factor-mimicking portfolios of the investment factor.

> Hypothesis 1b: The overlap emerges because lower investment leads to a decrease in the market value and thus to an increase in the book-to-market ratio whereas higher investment leads to an increase in the market value and thus to a decrease in the book-to-market ratio.

Following the reasoning behind our proposed channel, we further argue that stocks entering the value portfolio due to a decrease in their market values rather than due to an increase in their book values should be subject to the systematic risk associated with low investment. Therefore, we expect them to behave like conservative stocks, even if they are not (yet) identified as conservative stocks based on the most recent financial statements. This conclusion follows from our conjecture that a high book-to-market ratio that is down to a decrease in the market value is indicative of low investment. On the contrary, stocks that enter the growth portfolio due to an increase in their market values rather than due to a decrease in their book values should not be subject to the systematic risk associated with low investment and should thus behave like aggressive stocks. Again, this should also hold for those stocks that are not (yet) identified as aggressive stocks based on the most recent financial statements.

Consequently, stocks that enter the value portfolio due to a decrease in their market values should earn a premium over stocks that enter the growth portfolio due to an increase in their market values compensating the investors for the risk associated with low investment. By contrast, stocks that enter the value portfolio due to an increase in their book values should not earn a premium over stocks that enter the growth portfolio due to a decrease in their book values because they are not subject to the risk associated with low investment. Therefore, the outperformance of value stocks over growth stocks, i.e., the value premium, should be exclusively driven by i) value stocks that are simultaneously conservative stocks and/or enter the value portfolio due to a decrease in their market values, and ii) growth stocks that are simultaneously aggressive stocks and/or enter the growth portfolio due to an increase in their market values. On the other hand, the remaining value stocks should not outperform the remaining growth stocks.

Based on these considerations, we derive three further hypotheses:

> Hypothesis 2a: Stocks that enter the value portfolio due to a decrease in their market values earn a premium over stocks that enter the growth portfolio due to an increase in their market values. By contrast, stocks that enter the value portfolio due to an increase in their book values do not earn a premium over stocks that enter the growth portfolio due to a decrease in their book values.

> Hypothesis 2b: The value premium is driven by i) value stocks that are simultaneously conservative stocks and/or enter the value portfolio due to a decrease in their market values, and ii) growth stocks that are simultaneously aggressive stocks and/or enter the growth portfolio due to an increase in their market values.

> Hypothesis 2c: Stocks that enter the value portfolio due to a decrease in their market values are subject to the same risk as conservative stocks whereas stocks that enter the growth portfolio due to an increase in their market values are not subject to the risk associated with low investment.

The results of our empirical analysis confirm the derived hypotheses. We find that value (growth) stocks exhibit an excess overlap with the contemporaneous and the one-year ahead conservative (aggressive) stocks. This finding also holds for the stocks that just entered the value and growth portfolio. Moreover, our results indicate that this overlap is down to the fact that stocks primarily enter the value portfolio due to a decrease in their market values, whereas stocks primarily enter the growth portfolio due to an increase in their market values. Thereby, these value stocks subsequently exhibit low investment and these growth stocks subsequently exhibit high investment.

Furthermore, we find that stocks entering the value portfolio due to a decrease in their market values earn a significant monthly premium of 0.32% over stocks that enter the growth portfolio due to an increase in their market values. Moreover, even for those value stocks and growth stocks which are not (yet) conservative stocks or aggressive stocks, respectively, the 0.27% premium per month is still considerable and significant. However, both premia are mainly captured by large exposures to the investment factor, confirming that these value stocks behave like conservative stocks and these growth stocks like aggressive stocks. By contrast, stocks that enter the value portfolio due to an increase in their book values earn a significantly negative premium of 0.43% over stocks that enter the growth portfolio due to a decrease in their book values. This premium exhibits a small and insignificantly negative exposure to the investment factor, meaning that these value stocks do not behave like conservative stocks and are thus not subject to the risk associated with low investment.

Finally, when we exclude value stocks that are simultaneously conservative stocks and/or enter the value portfolio due to a decrease in their market values as well as growth stocks that are simultaneously aggressive stocks and/or enter the growth portfolio due to an increase in their market values from the factor-mimicking portfolio of the value factor, the value premium is only 0.08% per month and insignificant. This finding indicates that there is no-stand alone value premium that is independent of the investment premium.

The value factor rather seems to capture the same effect as the investment factor, only more timely but less accurately. This conclusion is consistent with the conjecture of Hou et al. (2015) that the value factor is a noisy version of the investment factor.

Overall, the findings of our study support the stance that the value factor should not be included in a factor pricing model. Therefore, we favor a more parsimonious asset pricing model, such as the q-factor model of Hou et al. (2015) or a version of the Fama-French five-factor model that excludes the value factor. This conclusion is in the spirit of Cochrane (2011) who advocates a reduction in the dimensionality of empirical asset pricing.

The remainder of the paper is structured as follows: Section 2 introduces our data set and describes our portfolio formation procedure, which is essentially the same as the procedure established by Fama and French (1993, 2015). Section 3 presents empirical results on the relation between the book-to-market ratio and investment as well as on the relation between the factor-mimicking portfolios of the value factor and the investment factor. In Section 4, we examine the returns of the different types of value and growth stocks and to which extent the investment factor can explain them. Finally, Section 5 concludes.

2 Construction of Factor Portfolios and Returns

For the formation of the factor portfolios, we closely follow the procedure established by Fama and French (1993, 2015). Thus, we use all common stocks from the CRSP monthly stock database that were listed on the NYSE, AMEX, or NASDAQ during our sample period from July 1963 to June 2018 (660 months) and have a CRSP share code of 10 or 11. For each stock, we obtain data on its monthly returns, its end-of-month prices, and its end-of-month number of shares outstanding. Moreover, we retrieve data on the stocks' company fundamentals from the Compustat North America annual fundamentals database as well as data on the one-month US Treasury Bill rate from Kenneth French's website.[2]

For the formation of the factor portfolios of the value factor, we sort the stocks in our sample at the end of June of each year from 1963 to 2017 into two groups according to their market equity (ME), which is stock price times shares outstanding at the end of June of the respective year, and into three groups according to their book-to-market ratio (B/M), which is book equity divided by market equity at the last fiscal year ending in the prior year.[3] The breakpoint for the ME sort is the median ME of all NYSE stocks in our sample at the end of June of the respective year. The breakpoints for the B/M sort are the 30th and 70th B/M percentiles of all NYSE stocks in our sample at the end of June of the respective year. Taking the intersections of the two ME groups and the three B/M groups yields six portfolios, whose returns are calculated each month as the value-weighted average returns of their stocks. The return on the value factor (HML return) for each month from July of the respective year to June of the subsequent year is calculated as the average return on the two high B/M portfolios (value return) in the respective month minus the average return on the two low B/M portfolios (growth return) in the respective month. Moreover, consistent with the calculation of the HML return, we form the HML portfolio as the long-short combination of the value portfolio and the growth portfolio, whereby the value portfolio is the equal-weighted combination of the two value-weighted high B/M portfolios and the growth portfolio is the equal-weighted combination of the two value-weighted low B/M portfolios.

The factor portfolios of the investment factor are formed in the same way as those of the value factor, only that the second sort is with respect to investment (INV), which is

[2] `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

[3] Following Fama and French (1993, 2015), we define book equity as the book value of stockholders' equity, plus, if available, balance sheet deferred taxes and investment tax credit, minus the book value of preferred stock (depending on availability, the redemption, liquidation, or par value of preferred stock is used, in that order); if the book value of stockholders' equity is not directly available, it is measured as the book value of common equity plus the par value of preferred stock or as the difference between the book value of total assets and the book value of total liabilities (in that order).

the change in total assets from the last fiscal year ending in the forelast year to the last fiscal year ending in the prior year, divided by total assets for the last fiscal year ending in the forelast year. The return on the investment factor (CMA return) for each month from July of the respective year to June of the subsequent year is calculated as the average return on the two low INV portfolios (conservative return) in the respective month minus the average return on the two high INV portfolios (aggressive return) in the respective month. Additionally, we form the CMA portfolio as the long-short combination of the conservative portfolio and the aggressive portfolio, whereby the conservative portfolio is the equal-weighted combination of the two value-weighted low INV portfolios and the aggressive portfolio is the equal-weighted combination of the two value-weighted high INV portfolios.

The average HML return across the period from July 1963 to June 2018 amounts to 0.31% and is statistically significant (2.86), while the average CMA return amounts to 0.27% (3.54), which is also significantly different from zero. The correlation between the two returns across the sample period is 0.72, and thus quite large.

3 The Relation between Value and Investment

3.1 Correlations and Portfolio Overlaps

Our theory, as outlined in the introduction, relies on the conjecture that a high book-to-market ratio is associated with low investment and that a low book-to-market ratio is associated with high investment. Therefore, Table 1 presents the average cross-sectional Pearson and Spearman correlations of the book-to-market ratio with the contemporaneous, past, and future asset growth rates.[4] In line with the formation of the factor portfolios, the book-to-market ratios and the asset growth rates are measured on the re-

[4]Note that the measure for investment is the asset growth rate from the forelast year to the prior year.

balancing dates at the end of each June. We present results for two stock groups: firstly, all stocks in our stock universe on the respective rebalancing date, and secondly, all stocks that are either in the value portfolio or in the growth portfolio (hf. HML stocks) on the respective rebalancing date.

INSERT TABLE 1 NEAR HERE

The results for the Pearson correlations reveal that for the entire stock universe, the average correlation between the book-to-market ratio and the one-year ahead asset growth rate is -0.15, and thus in absolute terms the highest within this category. Meanwhile, the correlation between the book-to-market ratio and the contemporaneous asset growth rate amounts only to -0.09. These results support our conjecture that the book-to-market ratio often leads the asset growth rate. Additionally, although not particularly pronounced, the findings are still indicative of a negative relation between the book-to-market ratio and the contemporaneous as well as the future asset growth rate. Moreover, the pattern is even more pronounced for HML stocks.

The Spearman correlations - which are arguably more important concerning the relation between the factor portfolios - are in absolute terms notably larger than the Pearson correlations. For the entire stock universe, the average correlation between the book-to-market ratio and the contemporaneous asset growth rate is -0.30. The average correlation with the one-year ahead asset growth rate is only slightly weaker. For the HML stocks, the correlations are in absolute terms again higher than for the entire stock universe. In particular, the book-to-market ratio exhibits correlations of -0.34 and -0.32 with the contemporaneous asset growth rate and with the one-year ahead asset growth rate, respectively.

Overall, these results support the conjecture that the book-to-market ratio and the asset growth rate are negatively related. Thereby, the book-to-market ratio is as expected not only negatively related to the contemporaneous but also to the one-year ahead asset growth rate. This finding confirms our conjecture that the change in the book-to-market ratio is frequently taken into account earlier for the formation of the factor portfolios than the associated change in investment. Moreover, although the Pearson correlations are rather moderate, the fact that the Spearman correlations are notably stronger, especially for the HML stocks, indicates that this negative relation is likely to induce a considerable overlap between the HML and the CMA portfolios.

Consequently, we next evaluate to what extent the negative relation between the book-to-market ratio and the asset growth rate translates into overlaps between the HML portfolio and the CMA portfolio. Table 2 presents the average excess overlaps of the value portfolio, the growth portfolio, and the HML portfolio with the contemporaneous, future, and past CMA portfolios. The excess overlap of the value (growth) portfolio with the CMA portfolio is calculated as the weighted percentage of value (growth) stocks that are in the respective conservative portfolio minus the weighted percentage of value (growth) stocks that are in the respective aggressive portfolio.[5] The excess overlap of the HML portfolio with the CMA portfolio is the excess overlap of the value portfolio with the CMA portfolio minus the excess overlap of the growth portfolio with the CMA portfolio, divided by 2.

INSERT TABLE 2 NEAR HERE

If the factor-mimicking portfolio of the value factor were independent of the factor-mimicking portfolio of the investment factor, we would expect to observe an excess overlap of zero. The results presented in Table 2 show that this is not the case. In particular, the value portfolio exhibits an excess overlap of 15.7% with the contemporaneous CMA portfolio, indicating that the weighted percentage of value stocks that are in the conservative portfolio is 15.7 percentage points higher than the weighted percentage of value stocks that are in the aggressive portfolio. Moreover, the excess overlap of the value portfolio with the one-year ahead CMA portfolio is 20.1% and thus even higher than with

[5]The weights applied to the value (growth) stocks correspond to the stocks' weights in the value (growth) portfolio on the respective rebalancing date (see Section 2).

the contemporaneous CMA portfolio. This overlap is only slightly lower in the following years.

On the contrary, the growth portfolio exhibits the highest absolute excess overlap of 35.6% with the contemporaneous CMA portfolio. Nevertheless, though somewhat less pronounced, there exists a considerable excess overlap of 31.8% between the growth portfolio and the one-year ahead CMA portfolio. Contrary to the value portfolio, the absolute excess overlap of the growth portfolio is notably lower for more than one-year ahead CMA portfolios.

Aggregating the results for the value portfolio and the growth portfolio shows that the HML portfolio exhibits the highest excess overlaps of 26.0% and 25.7% with the one-year ahead and the contemporaneous CMA portfolio, respectively. Moreover, the overlaps of the HML portfolio with the CMA portfolios decrease notably with increasing time distance. These findings confirm Hypothesis 1a that the HML portfolio has a considerable overlap with the contemporaneous as well as the one-year ahead CMA portfolio. Thus, value stocks are likely to be either simultaneously or in the subsequent year conservative stocks while growth stocks are likely to be either simultaneously or in the subsequent year aggressive stocks. Arguably, the fact that the value factor and the investment factor select to a considerable extent the same stocks in their long legs as well as in their short legs is potentially a major reason for the strong positive correlation between the returns of the two factors.

3.2 Changes in Book Equity, Market Equity, and Assets

Hypothesis 1b conjectures that the overlap between the HML portfolio and the CMA portfolio emerges because lower investment leads to a decrease in the market value and thus to an increase in the book-to-market ratio, whereas higher investment leads to an increase in the market value and thus to a decrease in the book-to-market ratio. In order to verify this hypothesis, we investigate the changes in book values, market values, book-to-market ratios, and assets of value and growth stocks. Thereby, we follow Daniel and Titman (2006) and apply the natural logarithm to decompose the changes in the book-to-market ratio into changes in the book value and changes in the market value:

$$log(\frac{B_{t+1}}{M_{t+1}}) - log(\frac{B_t}{M_t}) = log(\frac{B_{t+1}}{B_t}) - log(\frac{M_{t+1}}{M_t}), \tag{1}$$

where B_t is the book value at time t and M_t is the market value at time t. This equation allows us to attribute changes in the book-to-market ratio to changes in the book value and to changes in the market value.

INSERT TABLE 3 NEAR HERE

Table 3 shows the average log-changes in the book values, the market values, the book-to-market ratios, and the assets of value and growth stocks over the year before they enter the value and growth portfolios as well as over their first and second year in the portfolios. Thereby, we consider only value and growth stocks that already exist in our data set and have valid book value and market value data for the rebalancing date in the year before they enter the portfolios. For the calculation of the average log-changes, the stocks are weighted with the weights they receive in their first year in the respective portfolio (see Section 2), and the weights are scaled such that they add up to one.

We additionally compare the changes to two control groups in order to account for the long-term increases in book values, market values, and assets. This approach allows us to assess the detrended changes. The first control group comprises all stocks that are in the stock universe on the rebalancing date at which the value (growth) stocks enter the portfolio and that are already in the stock universe on the rebalancing date in the prior year.[6] The second control group contains all stocks that are in the stock universe on the rebalancing date at which the value (growth) stocks enter the value (growth) portfolio, that are already in the stock universe on the rebalancing date in the prior year, and that

[6]Note that this group also comprises the entering value and growth stocks themselves.

neither were in the value (growth) portfolio on the rebalancing date in the prior year nor enter the value (growth) portfolio. Thus, the second control group contains the stocks that could but did not enter the value (growth) portfolio. The stocks in both control groups are value-weighted based on the stocks' market values on the rebalancing date when the value and growth stocks enter the portfolios.

For the entering value stocks, the results in Panel A of Table 3 show that they experience an average log-increase in their book-to-market ratio of 0.41 over the year before they enter the value portfolio. This increase in the book-to-market ratio can be decomposed into an average log-increase in the book value of 0.15 and an average log-decrease in the market value of 0.25. Thus, in absolute terms, only about 40% of the change in the book-to-market ratio can be attributed to the change in the book value, whereas the remaining 60% can be attributed to the change in the market value.

This finding is even more pronounced in comparison to the control groups. Specifically, although the book-to-market ratios of the stocks in the two control groups do on average not increase, their book values exhibit average log-increases of 0.12 and 0.13, respectively, and their market values exhibit average log-increases of 0.13. Thus, the increases in their book values and market values nearly offset each other and are roughly consistent with the long-term market return. Moreover, one can ex-ante reasonably expect the entering value stocks to exhibit similar increases in their book values and market values as the stocks in the control groups. Therefore, we have to account for these expected changes in the book values and market values. Specifically, the entering value stocks exhibit, on average, only a 0.03 higher log-increase in their book values compared to the stocks in the two control groups. On the other hand, they exhibit, on average, a higher log-decrease of 0.38 and 0.39 in their market values compared to the first and second control group, respectively. This finding implies that the entry of the value stocks as compared to the control stocks is to more than 90% down to the stronger decrease in the market value. Thus, when taking the expected changes in the book values and market values into account, the increase in the average book-to-market ratio can be mainly attributed to the comparatively strong decrease in the market value. Furthermore, similar to the change in their book values, the entering value stocks' average log-change in assets is 0.14 and statistically not different from those of the control stocks. That is, on average, one cannot (yet) observe a particularly low investment for the entering value stocks in their financial statements.

However, as shown in Panel B of Table 3, the picture is very different for the entering value stocks' first year in the value portfolio. The new value stocks exhibit a log-increase in their market values that is, on average, 0.03 higher than that of the stocks in the entire stock universe as well as of the non-entering stocks. These differences are consistent with the positive value premium but are not statistically significant. On the other hand, the book values of the new value stocks exhibit a log-increase of on average only 0.01, which is significantly lower than the average log-increases of the stocks in the two control groups. Thus, the partial reversal of the new value stocks' book-to-market ratios is to around 75% down to the abnormally low increase in their book values. Additionally, the small average increase in the book values of the new value stocks is accompanied by an average log-increase in assets of only 0.05, which is significantly lower than the log-increases in assets of the stocks in the two control groups. This result indicates that the new value stocks are considerably more likely to become conservative stocks in the subsequent year than the remaining stocks.

Panel C of Table 3 shows that the patterns observed for new value stocks during their first year remain qualitatively the same during their second year, and are even quantitatively quite similar.[7] In particular, the new value stocks exhibit, on average, a slightly higher increase in their market values than the stocks in the control groups. By contrast, they experience, on average, almost no change in their book values, and therefore exhibit a significantly lower increase than the stocks in the control groups. This

[7]The results also remain similar for the third year (not reported).

leads to a further partial reversal in their book-to-market ratios. Additionally, the hardly existing change in the entering value stocks' book values is again accompanied by an average increase in their assets that is significantly lower than those of the stocks in the control groups. Thus, the entering value stocks exhibit a rather low investment in comparison to the other stocks.

In sum, entering value stocks seem to experience an increase in their book-to-market ratios primarily due to a decrease in their market values rather than an increase in their book values. This decrease in the market values and the associated increase in the book-to-market ratios are followed by an abnormally low increase in book values and assets in subsequent years. Thus, in line with our story, the market value decrease might be caused by market participants reducing their valuation after they learn that the firms invest less, which in turn takes some time to be reflected in financial statements. Consequently, these findings support Hypothesis 1b that lower investment leads to a decrease in the market value and to an increase in the book-to-market ratio. Moreover, due to the low asset growth during their first year in the value portfolio, the entering value stocks are more likely to be included in the conservative portfolio, and less like to be included in the aggressive portfolio in the subsequent year.

The results for entering growth stocks are similarly affirmative of Hypothesis 1b. They experience an average log-decrease of 0.53 over the year before they enter the growth portfolio. This decrease in the entering growth stocks' book-to-market ratios can be entirely attributed to the increase in their market values, whereas the slight increase in their book values even works against the decrease in their book-to-market ratios.

When comparing these changes to those of the control stocks, one can observe that the log-increase in the entering growth stocks' market values is on average by 0.42 and 0.46 higher compared to the first and second control group, respectively. By contrast, the log-increase in the entering growth stocks' book values is on average only 0.10 and 0.06 lower compared to the stocks in the two control groups. Thus, less than 20% of the decrease in the growth stocks' book-to-market ratios as compared to the control stocks can be attributed to the lower increase in their book values, whereas more than 80% can be attributed to the abnormally high increase in their market values. Furthermore, the entering growth stocks already exhibit a significantly higher log-change in their assets than the non-entering stocks over the year before their entry. This result indicates that the entering growth stocks are already more likely to become aggressive stocks in the year in which they enter the growth portfolio.

However, like for the value stocks, the patterns are entirely different in the years after the new growth stocks enter the growth portfolio. During their first year, the new growth stocks experience a log-increase in their book values of on average 0.18, which is 0.07 and 0.11 higher than those of the stocks in the first and second control group, respectively. The market values of the new growth stocks exhibit a log-increase of on average 0.10, which is not significantly different from those of the stocks in the two control groups. Thus, the higher increase in the book value is entirely responsible for the partial reversal in the new growth stocks' book-to-market ratios. Moreover, the increase in their book values and the reversal in their book-to-market ratios is accompanied by a substantial asset growth. Specifically, the new growth stocks exhibit a log-increase in their assets of 0.17, which is significantly higher than those of the stocks in the two control groups. Consequently, as they exhibit higher average asset growth rates, the entering growth stocks should be more likely to be included in the aggressive portfolio in the subsequent year compared to the remaining stocks.

The pattern for the growth stocks' second year in the growth portfolio is qualitatively again mostly identical to that of the stocks' first year. In particular, they experience an increase in their book values that is significantly higher than those of the stocks in the control groups. Since the increase in the new growth stocks' market values is only slightly and insignificantly lower than those of the stocks in the two control groups, the higher increase in their book values is primarily responsible for the reversal in their book-to-market ratios. The increases in the growth stocks' book values and book-to-market ratios are again accompanied by a considerably and significantly higher increase in their assets compared to the stocks in the control groups.

In sum, the entering growth stocks experience a decrease in their book-to-market ratios, primarily due to an abnormally high increase in their market values rather than due to a decrease in their book values. The increase in the market values and the decrease in the book-to-market ratios are followed by abnormally high increases in book values and assets over the subsequent years. Hence, the increase in market value might be driven by market participants that raise their valuation as soon as they learn that the firms increase their investment. As higher investment often takes time to be reflected in the financial statements and potentially remains systematically higher for some time, it is not entirely reflected immediately but can rather be observed for several years. The higher contemporaneous and future investment should make growth stocks more likely to be selected into the contemporaneous and the one-year ahead aggressive portfolio and less likely to be selected in the corresponding conservative portfolios. This finding supports the part of Hypothesis 1b that argues that higher investment leads to an increase in the market value and thus to a decrease in the book-to-market ratio.

3.3 Inclusion of Entering HML Stocks in the Investment Factor Portfolios

As outlined, we conclude from the evidence in Table 3 that entering value stocks should be more likely to become conservative stocks and less likely to become aggressive stocks in the following year than stocks that do not enter the value portfolio. On the opposite, entering growth stocks should be more likely to become aggressive stocks and less likely to become conservative stocks in the same or in the following year than stocks that do not enter the growth portfolio. Hypothesis 1b argues that these effects cause the excess overlap between the HML portfolio and the CMA portfolio.

INSERT TABLE 4 NEAR HERE

In order to verify these conjectures, we examine the excess overlaps with the contemporaneous, past, and future CMA portfolios of entering value (growth) stocks as well as of the stocks that could but did not enter the value (growth) portfolio. The excess overlaps for the HML stocks are calculated as the excess overlaps for the value stocks minus the excess overlaps for the growth stocks, divided by 2. Panel A of Table 4 presents the results. Consistent with the evidence in Table 3, the excess overlap of 1.6% with the contemporaneous CMA portfolio shows that the entering value stocks are not more likely to be in the conservative portfolio than to be in the aggressive portfolio. However, the negative excess overlap of the entering value stocks of more than 10% with the past CMA portfolios indicates that a substantial fraction of the stocks that enter the value portfolio move out of the aggressive portfolio and/or into the conservative portfolio. Moreover, in the year after they enter the value portfolio, they are by 18.5 percentage points more likely to be in the conservative portfolio than in the aggressive portfolio. This result implies that a considerable fraction of new value stocks move out of the aggressive portfolio and/or into the conservative portfolio in the year after they enter the value portfolio.

By contrast, the excess overlaps between the stocks that do not enter the value portfolio and the CMA portfolios remain quite constant, which indicates that stocks not entering the value portfolio do not systematically move out of the aggressive portfolio and/or into the conservative portfolio. This finding confirms our conjecture stating that entering value stocks are more likely to be selected into the conservative portfolio and less likely to be selected into the aggressive portfolio than the remaining stocks.

For the entering growth stocks, Table 4 reveals that they already exhibit a considerable excess overlap of 16.7% with the contemporaneous CMA portfolio. This finding stands in contrast to the almost zero overlap between new value stocks and the contemporaneous CMA portfolio but is consistent with the results from Table 3 that entering growth stocks already exhibit a comparatively high asset growth when they enter the growth portfolio. Additionally, the absolute excess overlap with the contemporaneous CMA portfolio is again higher than the excess overlaps with the past CMA portfolios and further increases to 27.8% for the one-year ahead CMA portfolio. These results indicate that the entering growth stocks systematically move out of the conservative portfolio and/or into the aggressive portfolio in the same and subsequent year in which they enter the growth portfolio.

This pattern cannot be observed for the stocks that do not enter the growth portfolio. If anything, these stocks rather display the opposite pattern, i.e. they move out of the aggressive portfolio and/or into the conservative portfolio. However, this pattern is not particularly pronounced. These results confirm the conjecture based on the results in Table 3 that entering growth stocks are more likely to be selected into the aggressive portfolio and less likely to be selected into the conservative portfolio.

Aggregating the results for the entering value and growth stocks shows that the entering HML stocks exhibit an excess overlap of 9.1% with the contemporaneous CMA portfolio. This represents a substantial increase compared to the slightly negative excess overlaps with the past CMA portfolios. Moreover, the excess overlap even further increases to 23.2% for the one-year ahead CMA portfolio. This finding strongly suggests that the excess overlap between the HML portfolio and the CMA portfolio observed in Table 2 is to a large extent driven by entering value and growth stocks moving out of the aggressive (conservative) portfolio and into the conservative (aggressive) portfolio, especially in the year after their entry.

Hypothesis 1b suggests that stocks that enter the value and growth portfolios due to a change in their market values rather than due to a change in their book values primarily cause the excess overlap. In order to examine whether this holds, we split the entering value stocks into two groups. The first group contains those stocks that enter the value portfolio primarily due to a decrease in their market values (hf. ME value stocks). Thereby, an entering value stock is a ME value stock if the excess log-decrease in its market value is higher than the excess log-increase in its book value. An excess log-change is calculated as the log-change of the stock minus the value-weighted average log-change of all stocks in the stock universe (i.e. these stocks correspond to the first control group in Section 3.2).[8] The second group is the complement of the first group, i.e. stocks that enter the value portfolio primarily due to an increase in their book values (hf. BE value stocks), which are identified as the entering value stocks for which the excess log-increase in book value is higher than the excess log-decrease in market value. Analogously, we also split the entering growth stocks into two groups. The first group contains the growth stocks that enter the growth portfolio primarily due to an increase in their market values (hf. ME growth stocks), identified as the entering growth stocks for which the excess log-increase in market value is higher than the excess log-decrease in book value. The second group is again the complement, i.e. growth stocks that enter the growth portfolio primarily due to a decrease in their book values (hf. BE growth stocks), identified as the entering growth stocks for which the excess log-decrease in book value is higher than the excess log-increase in market value.

For the ME value stocks, Panel B of Table 4 shows that the excess overlap increases in particular from the one-year lagged CMA portfolio to the contemporaneous CMA portfolio, namely from -9.0% to 13.2%. Moreover, the excess overlap further increases to 20.9% for the one-year ahead CMA portfolio. By contrast, the BE value stocks, which have similar excess overlaps with the past CMA portfolios, exhibit a substantial negative excess overlap with the contemporaneous CMA portfolio of -56.6%. That is, the entire positive excess overlap between the entering value stocks and the contemporaneous CMA portfolio is down to ME value stocks. Yet, the negative excess overlap of the BE value stocks with the contemporaneous CMA portfolio completely reverses in the following year such that the excess overlap of the BE value stocks with the one-year ahead CMA

[8] We choose this definition in order to mitigate the impact of market-wide trends in book value changes and market value changes. However, our results are qualitatively the same if we take the raw log-changes rather than the excess log-changes.

portfolio amounts to 1.7%. Nevertheless, this means that BE value stocks still contribute very little to the excess overlap between the HML portfolio and the one-year ahead CMA portfolio.

For the ME growth stocks, the results reveal that the absolute excess overlap considerably increases from -11.4% to -31.1% for the contemporaneous CMA portfolio. The absolute excess overlap further increases to -37.8% for the one-year ahead CMA portfolio. Interestingly, this increase is like for the ME value stocks again notably less pronounced than from the one-year lagged to the contemporaneous CMA portfolio. By contrast, the BE growth stocks exhibit a considerable excess overlap of 44.9% with the contemporaneous CMA portfolio. This excess overlap decreases for the one-year ahead CMA portfolio, but is with 20.0% still relatively high, indicating that it still works against the positive overlap between the HML portfolio and the CMA portfolio. Hence, the ME growth stocks are entirely responsible for the negative excess overlap between the entering growth stocks and the contemporaneous as well as the one-year ahead CMA portfolio whereas the BE growth stocks work against this overlap.

For the aggregate of the ME value stocks and the ME growth stocks (hf. ME HML stocks) the results show that their excess overlap with past CMA portfolios is close to zero, but that it considerably increases to 22.1% for the contemporaneous CMA portfolio and further to 29.4% for the one-year ahead CMA portfolio. On the contrary, the excess overlap of the aggregate of the BE value stocks and the BE growth stocks (hf. BE HML stocks) is already negative for the one-year lagged CMA portfolio and further decreases to -50.8% for the contemporaneous CMA portfolio. Moreover, although the excess overlap subsequently considerably reverses, it is with -9.2% still negative for the one-year ahead CMA portfolio.

Combining these results shows that the positive excess overlap of the entering HML stocks with the contemporaneous and the one-year ahead CMA portfolio is entirely down to the ME HML stocks. Thus, this finding confirms the final part of Hypothesis 1b, namely that the ME value stocks and the ME growth stocks are responsible for the excess overlap between the HML portfolio and the CMA portfolio. On the contrary, the BE HML stocks do not only fail to contribute but even counteract the positive excess overlap with their negative excess overlaps. In particular, due to their strongly negative overlap with the contemporaneous CMA portfolio, they are the reason why the excess overlap of the entering HML stocks with the contemporaneous CMA is only 9.1%, and thus much lower than their excess overlap with the one-year ahead CMA portfolio of 23.2%. This substantial negative overlap between the BE HML stocks and the one-year ahead CMA portfolio is neither inconsistent with nor predicted by our theory. A potential explanation is that the BE value firms are firms that make acquisitions that are not appreciated by the market, wherefore the book values and assets strongly increase while market values increase less. On the other hand, BE growth firms might be firms that conduct spin-offs that are appreciated by the market, wherefore book values and assets strongly decrease while market values decrease less. This reasoning would be in line with a conglomerate discount (e.g. Berger and Ofek (1995)).

4 Return Premia

4.1 Returns to Entering Value and Growth Stocks

In Section 3, we confirm that stocks entering the value and growth portfolios due to a change in their market values are responsible for the overlap between the HML portfolio and the CMA portfolio. Thereby, especially the excess overlap between the HML portfolio and the one-year ahead CMA portfolio implies that - no matter whether already reflected in financial statements or not - ME value stocks frequently exhibit low investment and ME growth stocks frequently exhibit high investment. Consequently, ME value stocks should be subject to the risk associated with low investment, while ME growth stocks should not be subject to the risk associated with low investment. In line with this inference, Hypothesis 2a argues that ME value stocks can be expected to earn a premium over ME growth stocks and that this should especially hold as well for those ME value stocks that are not (yet) conservative stocks.

On the contrary, Table 4 shows that BE value stocks are more frequently aggressive than conservative stocks while BE growth stocks are more frequently conservative than aggressive stocks. Therefore, BE value stocks should not be subject to the same risk as conservative stocks and should thus, in accordance with Hypothesis 2a, not earn a premium over BE growth stocks. One might even suspect BE growth stocks to be subject to the same risk as conservative stocks, implying that they might earn a premium over BE value stocks.

In order to investigate these implications, we determine value (growth) returns using only i) stocks that enter the value (growth) portfolio, ii) stocks that enter the value (growth) portfolio primarily due to a decrease (increase) in their market values, and iii) stocks that enter the value (growth) portfolios primarily due to an increase (decrease) in their book values.[9] From these modified value and growth returns, we obtain in turn the HML returns for the entering value and growth stocks, for the entering ME value and ME growth stocks (ME HML return), and for the entering BE value and BE growth stocks (BE HML return).

INSERT TABLE 5 NEAR HERE

The results for the average value, growth, and HML returns for the three cases are displayed in Panel A of Table 5. We are particularly interested in how the entering ME value and ME growth stocks compare to all entering value and growth stocks as well as to the entering BE value and BE growth stocks. Therefore, we additionally show the average excess returns of the ME value return, the ME growth return, and the ME HML return over the corresponding returns for all entering stocks and for stocks that enter the

[9]The remaining portfolio formation procedure is identical to the approach as outlined in Section 2. In particular, the breakpoints for the ME and B/M sorts remain the same as in the construction of the usual value and growth portfolios.

value and growth portfolios due to a change in their book values.

We find that the average ME HML return is significant and amounts to 0.32% per month. This result confirms the prediction of Hypothesis 2a that stocks that enter the value portfolio due to a decrease in their market values earn a premium over stocks that enter the growth portfolio due to an increase in their market values. Furthermore, the ME value return outperforms the value return of all entering value stocks, and the ME growth return underperforms the growth return of all entering growth stocks. While both differences are marginally insignificant, the aggregated ME HML return significantly outperforms the HML return of all entering stocks on average by 0.09% per month.

Moreover, as already implied by the comparison with the returns for all entering stocks, the ME value return substantially and significantly outperforms the BE value return, and the ME growth return substantially and significantly underperforms the BE growth return. Consequently, the ME HML return significantly outperforms the BE HML return on average by 0.74% per month, and the BE HML return exhibits a significantly negative average of -0.43%. On the one hand, this finding confirms the second part of Hypothesis 2a that stocks entering the value portfolio due to an increase in their book values do not earn a premium over stocks entering the growth portfolio due to a decrease in their book values. On the other hand, the result that the average BE HML return is substantially and significantly negative is - though not inconsistent - not necessarily implied by our story. A likely reason might be the substantial overlap between BE value and aggressive stocks as well as between BE growth and conservative stocks (as displayed in Panel B of Table 4). Thus, the positive premium of conservative over aggressive stocks might turn into a negative premium of BE value stocks over BE growth stocks.

Also, Panel B of Table 4 shows a substantial overlap between the ME HML stocks and the contemporaneous CMA portfolio. Therefore, the significant premium of the ME value stocks over the ME growth stocks might be down to those ME value and ME growth stocks that are already conservative respectively aggressive stocks and thus earn the investment premium. However, our story implies that ME value stocks that are not (yet) conservative stocks and/or for which no substantial decrease in investment is (yet) reflected in the financial statements should also already earn a premium. Therefore, we further divide the ME value stocks into two groups. The first group contains only stocks that contemporaneously neither are in the conservative portfolio nor moved out of the aggressive portfolio (hf. ME no-INV value stocks). The second group contains the remaining ME value stocks, i.e. those that are either in the conservative portfolio or moved out of the aggressive portfolio (hf. ME INV value stocks). Analogously, we also partition the ME growth stocks into two groups. The first group contains only ME growth stocks that contemporaneously neither are in the aggressive portfolio nor moved out of the conservative portfolio (hf. ME no-INV growth stocks). The second group contains the remaining ME growth stocks, i.e. those that are either in the aggressive portfolio or moved out of the conservative portfolio (hf. ME INV growth stocks). Likewise, we also identify the BE value stocks that contemporaneously neither are in the conservative portfolio nor moved out of the aggressive portfolio (hf. BE no-INV value stocks), and the BE growth stocks that contemporaneously neither are in the aggressive portfolio nor moved out of the conservative portfolio (hf. BE no-INV growth stocks).

The average monthly value, growth, and HML returns for the subgroups are presented in Panel B of Table 5. Additionally, as our particular focus is on the ME no-INV value stocks, the ME no-INV growth stocks, and their HML return (hf. ME no-INV HML return), we compare the other returns to the corresponding ME no-INV returns. The results reveal that there exists an average monthly ME no-INV HML return of 0.27% that is only marginally significant but - given that it is only slightly lower than the original HML return of 0.30% - economically considerable. Hence, this finding supports the implication of Hypothesis 2a that stocks that enter the value portfolio primarily due to a decrease in their market values but not (yet) exhibit a low(er) investment should nevertheless earn a premium over stocks that enter the growth portfolio primarily due to an increase in their market values but not (yet) exhibit a high(er) investment.

Moreover, the average ME INV HML return amounts to 0.34%, which is only by insignificant 0.07% higher than the ME no-INV HML return. That is, the HML return constructed from ME value (growth) stocks that already exhibit low (high) investment is only slightly higher than the HML return constructed from entering ME value (growth) stocks that do not (yet) exhibit low (high) investment. This result is reassuring for our conjecture that the ME no-INV HML stocks capture the same effect as the ME INV HML, which in turn capture the same effect as the investment factor.

Furthermore, like the BE HML return, the average BE no-INV HML return is with 0.40% per month significantly negative, and underperforms the ME no-INV HML return by substantial and highly significant 0.66% per month. This result confirms that the second part of Hypothesis 2a also holds for the no-INV subgroup.

4.2 Relevance of Entering HML Stocks and of CMA Stocks for the Value Premium

Our results in Section 4.1 confirm the existence of a positive and significant value premium for stocks entering the HML portfolio primarily due to a change in their market values whereas stocks that enter the HML portfolio primarily due to a change in their book values earn a significantly negative value premium. Moreover, these findings also hold for stocks that do not (yet) exhibit a substantial change in investment. We next examine the relevance of the premia of these subgroups for the value premium in general. To this end, we individually exclude the various subgroups from the construction of the value factor as described in Section 2.

Additionally, since the value premium is, due to the considerable excess overlap between the HML portfolio and the CMA portfolio, likely to be to a substantial extent driven by the same stocks as the investment premium, we determine a modified value factor that aims to be neutral with respect to the CMA stocks. Specifically, we consider for the formation of the value (growth) portfolio only stocks that are not at the same time in the conservative (aggressive) portfolio. From the modified value and growth portfolios, we obtain modified value and growth returns, and in turn a modified HML return (hf. INV-neutral HML return). Like, for the standard HML return, we also examine the relevance of the various groups of stocks for the INV-neutral value factor by excluding them individually from the construction of the INV-neutral value factor.

INSERT TABLE 6 NEAR HERE

The results are presented in Table 6. The standard HML return earns on average 0.30% per month and is statistically significant, whereas the INV-neutral HML return earns on average 0.14% per month and is statistically insignificant. Moreover, if we exclude the stocks used for the INV-neutral HML return, i.e. we only use value (growth) stocks that are simultaneously conservative (aggressive) stocks, the HML return amounts on average to 0.45% per month, significantly outperforming the standard HML return by 0.15% per month. This finding shows that the standard value premium is considerably driven by conservative and aggressive stocks, and thus by the investment premium.

Furthermore, the standard HML return remains unaffected by the exclusion of any of ME HML, ME INV HML, or ME no-INV HML stocks. The reason for this is that they account only for on average 16.5%, 8.3%, and 8.2%, respectively, of the entire HML portfolio and that their average HML returns are similar to the standard HML return. By contrast, although they make up on average only 3.4% and 2.8% of the entire HML portfolio, the exclusion of both, BE HML stocks as well as BE no-INV HML stocks, lead to a small but highly significant increase of 0.02% in the average HML return. This effect is down to the strongly negative HML return of -0.43% for BE HML stocks and -0.40% for BE no-INV HML stocks, respectively.

The INV-neutral HML return is more affected than the standard HML return. When we exclude the ME HML stocks, the monthly average decreases significantly by 0.05% to 0.08% and is statistically insignificant. That is, if the conservative and the ME value stocks, which we argue to be inherent conservative stocks, are excluded from the value portfolio and simultaneously the aggressive and the ME growth stocks, which we argue to be inherent aggressive stocks, are excluded from the growth portfolio, the value premium decreases by almost three fourth and is no longer statistically significant. This strongly supports Hypothesis 2b that the value premium is driven by value stocks that are simultaneously conservative stocks and/or enter the value portfolio due to a decrease in their market values as well as growth stocks that are simultaneously aggressive stocks and/or enter the growth portfolio due to an increase in their market values. Thus, the standard value premium seems to be mostly a compensation for the risk associated with low investment. Therefore, there does not seem to be a stand-alone value premium. This finding is in line with the conjecture of Hou et al. (2015) that the value factor is just a noisy version of the investment factor. Unsurprisingly, since the ME INV HML stocks contain primarily conservative value stocks and aggressive growth stocks, both of which are already excluded from the INV-neutral HML portfolio, the further decrease in the INV-neutral return beyond the decrease as compared to the standard HML return is primarily caused by the exclusion of ME no-INV HML stocks.

By contrast, if we exclude the BE HML stocks or the BE no-INV HML stocks, the INV-neutral HML return increases significantly by 0.03% per month to 0.17% and thereby restores its significance. This effect is again down to the strongly negative value premia of these stocks and thus not surprising.

4.3 Pricing of Returns

As shown in Section 4.1, there exists a positive and significant ME HML return. Hypothesis 2c argues that stocks entering the value portfolio due to a decrease in their market values are subject to the same risk as conservative stocks whereas stocks entering the growth portfolio due to an increase in their market values are, like aggressive stocks, not subject to the risk associated with low investment. Thus, as previously stated, we suggest that the significantly positive ME HML return is a compensation for the risk associated with low investment. This should particularly hold as well for the ME no-INV HML return.

In this part, we examine these conjectures by applying the Fama-French five-factor model without the value factor to the explanation of the various HML returns from Table 5. Specifically, our employed factor pricing model includes the market factor, the size factor, the profitability factor, and the investment factor from the Fama-French five-factor model.[10] For comparison purposes, we additionally determine the exposures of the standard HML return and the INV-neutral HML return.

INSERT TABLE 7 NEAR HERE

The results of the asset pricing tests are presented in Table 7. Consistent with the finding of Fama and French (2015), the standard HML return exhibits a slightly negative but insignificant intercept of -0.06% per month, indicating that its average return of 0.30% per month is entirely explained by the four factors. Thereby, the return is primarily captured by a strong positive and significant exposure to the investment factor and a moderate positive but still significant exposure to the profitability factor. This finding implies that the HML return can be interpreted mainly as a compensation for the risk associated with low investment and to a lesser extent as a compensation for the risk associated with high profitability.

The INV-neutral HML return also exhibits a slightly negative but insignificant intercept as well as a large positive exposure to the investment factor and a moderately positive exposure to the profitability factor. Thus, although the INV-neutral HML portfolio contains no conservative stocks in its long leg and no aggressive stocks in its short leg, it is still primarily captured by the investment factor. This result implies that a large part of the positive exposure of the standard HML return is not driven by the excess overlap

[10]The investment factor is constructed as described in Section 2. The construction of the remaining factors is described in Appendix A.

between the HML portfolio and the contemporaneous CMA portfolio. It rather indicates that value stocks that are not conservative stocks nevertheless behave like conservative stocks and are thus subject to the same risk as conservative stocks. Likewise, growth stocks that are not aggressive stocks seem to behave like aggressive stocks, implying that they are not subject to the risk associated with low investment.

The HML return that is constructed using only the entering value and growth stocks exhibits a slightly negative and insignificant intercept. Moreover, the average return of 0.23% per month is also primarily captured by a large positive exposure to the investment factor. Yet, the return also has a small but significant exposure to the size factor, whereas its exposure to the profitability factor is lower. The results for the ME HML return and the BE HML return show that the former also has a large positive exposure to the investment factor, whereas the latter has an insignificantly negative exposure to the investment factor. This finding suggests that the large positive exposure of the entering HML stocks' return to the investment factor is entirely down to the large positive exposure of the ME HML return.

Additionally, the ME HML return's large exposure to the investment factor is as well mainly responsible for capturing its average return of 0.32% per month, whereas its small exposures to the size and profitability factors contribute only little to the explanation. The large positive exposure to the investment factor implies that value stocks entering the value portfolio primarily due to a decrease in their market values behave like conservative stocks, whereas growth stocks entering the growth portfolio primarily due to an increase in their market values behave like aggressive stocks. This finding confirms Hypothesis 2c, which states that stocks entering the value portfolio due to a decrease in their market values are subject to the risk associated with low investment while stocks entering the growth portfolio due to an increase in their market values are, like aggressive stocks, not subject to the risk associated with low investment. Consequently, we can conclude that the significantly positive ME HML return is a compensation for the risk associated with low investment.

Nevertheless, in order to ensure that these findings are not only driven by the conservative and aggressive stocks contained in the ME HML stocks, we additionally examine the exposures of the ME INV HML return and of the ME no-INV HML return. Unsurprisingly, the ME INV HML return exhibits a substantial exposure to the investment factor, which almost completely captures the average return of 0.34% per month. Therefore, the same conclusions as for the ME HML return apply to the ME INV HML return. Furthermore, although its long-short portfolio does not contain any conservative stocks in its long leg and any aggressive stocks in its short leg, the ME no-INV HML return also exhibits a large exposure to the investment factor. This result supports our conjecture that ME value stocks that are not (yet) conservative stocks nevertheless behave like conservative stocks. Therefore, they should also be subject to the same risk as conservative stocks. Like the ME HML return as well as the ME INV HML return, the ME no-INV HML return thus also seems to be primarily a compensation for the risk associated with low investment.

As mentioned before, the BE HML return exhibits a negative and insignificant exposure to the investment factor. This finding indicates that BE value stocks are, contrary to ME value stocks, not subject to the same risk as conservative stocks, which explains why they do not earn a premium as compensation for the risk associated with low investment. However, the slightly negative exposure to the investment factor is not sufficient to capture the BE HML average return of -0.43% per month. It rather leaves a significantly negative intercept of -0.40% per month. Based on the strong negative excess overlap between the BE HML stocks and the contemporaneous CMA portfolio shown in Table 4, we would have expected a much more negative exposure to the investment factor which is able to capture the strongly negative average BE HML return. Therefore, the negative intercept is somewhat puzzling. Moreover, results for the BE no-INV HML return are very similar, only that the negative exposure to the investment factor is larger and significant, which leads to a smaller and insignificant intercept.

5 Conclusion

In this work, we put forward an explanation for the close relation between the value factor and the investment factor of the Fama-French five-factor model as documented by Fama and French (2015). Specifically, following the conclusion of Fama and French (2015) and Hou et al. (2015) that firms with lower investment are, all else equal, riskier, we argue that rational market participants that observe a decrease (increase) in a firm's investment perceive the firm as riskier (less risky). Consequently, they adjust their valuations of the firm downwards (upwards), and thereby cause an increase (decrease) in the firm's book-to-market ratio. This channel implies a negative relation between the book-to-market ratio and investment, and thus a positive relation between the factor-mimicking portfolios of the value factor and the investment factor. Moreover, in comparison to a change in the book-to-market ratio, a change in investment is only reflected in financial statements with a considerable lag. Therefore, we also examine the intertemporal relation between the factor-mimicking portfolios of the value factor and the investment factor.

In support of our theory, we find that there is a negative relation of the book-to-market ratio with contemporaneous and one-year ahead investment as well as an excess overlap of the factor-mimicking portfolio of the value factor with the contemporaneous and the one-year ahead factor-mimicking portfolios of the investment factor. Our results confirm that these relations are driven by stocks that experience an increase (decrease) in the book-to-market ratio due to a decrease (increase) in their market values.

Moreover, high book-to-market stocks that experienced an increase in their book-to-market ratios due to a decrease in their market values earn a positive return premium and behave like low investment stocks, implying that they are subject to the risk associated with low investment. By contrast, high book-to-market stocks that experienced an increase in their book-to-market ratios due to an increase in their book values earn a negative return premium and do not behave like low investment stocks, suggesting that they are not subject to the risk associated with low investment. Additionally, we find that the value premium is primarily driven by the excess return of the aggregate of low investment stocks and of high book-to-market stocks experiencing a decrease in their market values over the aggregate of high investment stocks and of low book-to-market stocks experiencing an increase in their market values.

In sum, these findings suggest that the value factor is not a risk factor on its own but rather a more timely but less accurate version of the investment factor. This lends evidence to the conjecture of Hou et al. (2015) that the value factor is a noisy version of the investment factor. For this reason, we support the stance that the value factor should not be included in a factor pricing model. We rather favor a more parsimonious asset pricing model such as the q-factor model of Hou et al. or a version of the Fama-French five-factor model that excludes the value factor.

For future research, we recommend to include only factors that can be profoundly motivated by economic theory. Prime examples for such factors are the profitability factor and the investment factor, both of which are well-motivated by Fama and French (2015) and Hou et al. (2015). Moreover, in addition to this standard recommendation, our findings suggest that - even if a new factor can be motivated by economic theory - it is important to make sure that this new factor is not just a different version of an already existing factor but rather captures another underlying effect.

Finally, although our results are in line with a risk-based explanation, we cannot rule out that behavioral aspects might also play a role. In particular, a high (low) book-to-market ratio due to a decrease (increase) in market value might be down to an overreaction of investors to a negative (positive) event, whereby the excess decrease (increase) in the market value reverses through higher (lower) future returns. However, since most findings such as the excess overlap between the factor-mimicking portfolios of the value factor and the investment factor are not necessarily implied by a behavioral explanation, we conclude that our results are much more consistent with a risk-based explanation and should be only slightly affected by behavioral aspects.

Appendix A: Construction of Factor Portfolios and Returns

The market portfolio in a given month is the value-weighted portfolio of all stocks in our data sample that have valid return and market equity (stock price times shares outstanding) data for the given month. The return on the market factor (MP) for the given month is the return on the market portfolio in the month minus the one-month T-Bill rate in the same month. The factor portfolios of the profitability factor are formed in the same way as those of the value factor (see Section 2), only that the second sort is with respect to operating profitability (OP), which is calculated as operating profits divided by book equity for the last fiscal year ending in the prior year. Operating Profits are defined as annual revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses. Book equity is the book equity as calculated for the book-to-market ratio (see footnote 2) plus minority interest. The OP data is considered to be valid if revenues data and cost of goods sold data for the last fiscal year ending in the prior year are available and the book equity for the last fiscal year ending in the prior year is positive. The return on the profitability factor (RMW) for each month from July of the respective year to June of the subsequent year is calculated as the average return on the two high OP portfolios (robust return) in the respective month minus the average return on the two low OP portfolios (weak return) in the respective month. The return on the size factor (SMB) for each month from July of a given year to June of the subsequent year is calculated as the average return on the nine low ME portfolios constructed for the value factor, the investment factor, and the profitability factor in the respective month minus the average return on the nine high ME portfolios constructed for the factors in the respective month.

Appendix B: Definitions

Value stocks

Stocks of high book-to-market firms

Growth stocks

Stocks of low book-to-market firms

HML stocks

Aggregate of value stocks (long) and growth stocks (short)

ME value stocks

Stocks that enter the value portfolio primarily due to a decrease in their market values

ME growth stocks

Stocks that enter the growth portfolio primarily due to an increase in their market values

ME HML stocks

Aggregate of ME value stocks (long) and ME growth stocks (short)

ME no-INV value stocks

ME value stocks that contemporaneously neither are in the conservative portfolio nor moved out of the aggressive portfolio

ME no-INV growth stocks

ME growth stocks that contemporaneously neither are in the aggressive portfolio nor moved out of the conservative portfolio

ME no-INV HML stocks

Aggregate of ME no-INV value stocks (long) and ME no-INV growth stocks (short)

ME INV value stocks

ME value stocks that are either in the conservative portfolio or moved out of the aggressive portfolio

ME INV growth stocks

ME growth stocks that are either in the aggressive portfolio or moved out of the conservative portfolio

ME INV HML stocks

Aggregate of ME INV value stocks (long) and ME INV growth stocks (short)

BE value stocks

Stocks that enter the value portfolio primarily due to an increase in their book values

BE growth stocks

Stocks that enter the growth portfolio primarily due to a decrease in their book values

BE HML stocks

Aggregate of BE value stocks (long) and BE growth stocks (short)

BE no-INV value stocks

BE value stocks that contemporaneously neither are in the conservative portfolio nor moved out of the aggressive portfolio

BE no-INV growth stocks

BE growth stocks that contemporaneously neither are in the aggressive portfolio nor moved out of the conservative portfolio

BE no-INV HML stocks

Aggregate of BE no-INV value stocks (long) and BE no-INV growth stocks (short)

Conservative stocks

Stocks of low investment firms

Aggressive stocks

Stocks of high investment firms

CMA stocks

Aggregate of conservative stocks (long) and aggressive stocks (short)

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Table 1
Correlation between Book-to-Market Ratio and Asset Growth

This table presents the average cross-sectional Pearson and Spearman correlations of the book-to-market ratio with the contemporaneous, the future (up to three years), and the past (up to three years) asset growth rates. The firm's book-to-market ratios are measured at the end of each June from 1963 to 2017 as the firm's book equity divided by the firm's market equity at the last fiscal year ending in the prior year. The firm's asset growth rates are measured at the end of each June from 1963 to 2017 as the change in the firm's total assets from the last fiscal year ending in the forelast year to the last fiscal year ending in the prior year, divided by the firm's total assets for the last fiscal year ending in the forelast year. The average correlations are shown for two different subsamples: all stocks in the stock universe (Stock Universe) at the respective date and stocks that are either in the value portfolio or in the growth portfolio (HML Stocks) at the respective date.

	Pearson		Spearman	
Year	Stock Universe	HML Stocks	Stock Universe	HML Stocks
-3	-0.04	-0.05	-0.13	-0.14
-2	-0.05	-0.06	-0.16	-0.18
-1	-0.07	-0.08	-0.22	-0.25
0	-0.09	-0.11	-0.30	-0.34
1	-0.15	-0.17	-0.27	-0.32
2	-0.10	-0.12	-0.19	-0.23
3	-0.08	-0.09	-0.14	-0.17

Table 2
Overlaps of HML Stocks with CMA Portfolios

This table presents the average excess overlaps of the value portfolio, the growth portfolio, and the HML portfolio with the contemporaneous, the future (up to three years), and the past (up to three years) CMA portfolios. The portfolios are formed as outlined in Section 2 at the end of each June from 1963 to 2017. For the value and the growth portfolios, an average excess overlap is the average percentage of value respectively growth stocks that are included in the long leg of the respective CMA portfolio minus the average percentage of value respectively growth stocks that are included in the short leg of the respective CMA portfolio. The percentages are weighted percentages, whereby the weights correspond to the stocks' weights in the respective portfolio at the respective rebalancing date. The average excess overlaps of the HML portfolio with the CMA portfolios are calculated as the average excess overlaps of the value portfolio with the CMA portfolios minus the average excess overlaps of the growth portfolio with the CMA portfolios, divided by 2.

Year	Value	Growth	HML
-3	1.5%	-26.4%	13.9%
-2	4.1%	-28.1%	16.1%
-1	9.3%	-31.5%	20.4%
0	15.7%	-35.6%	25.7%
1	20.1%	-31.8%	26.0%
2	19.6%	-21.1%	20.4%
3	18.9%	-14.0%	16.5%

Table 3
Changes in Book Value, Market Value, Book-to-Market Ratio, and Assets

Panel A of this table presents the time-averages of the cross-sectional average log-changes of newly entering value stocks and growth stocks (Incomers) in their book values (logBE), their market values (logME), their book-to-market ratios (logBM), and their assets (logAT) during the year prior to their inclusion in the value and growth portfolio, respectively. The firms' book values, market values, book-to-market ratios, and assets are measured at the end of each June from 1963 to 2017 based on the financial statements for their last fiscal year endings in the prior year. A log-change is the logarithm of the respective figure in a given year minus the logarithm of the respective figure in the prior year. The cross-sectional averages are weighted averages, whereby the weights correspond to the stocks' weights they receive when they enter the respective portfolio, scaled to sum to one. The cross-sectional average log-changes of value and growth stocks are compared to the cross-sectional average log-changes i) of the stocks in the entire stock universe (Stock Universe) at the respective portfolio rebalancing date, and ii) of the stocks that could but do not newly enter the value portfolio respectively the growth portfolio (Non-Incomers) at the respective portfolio rebalancing date. The cross-sectional averages of the Stock Universe and of the Non-Incomers are weighted averages, whereby the weights correspond to the stocks' market values at the respective portfolio rebalancing date. Panel B and C present the same results for the stocks' first year and second year in the respective portfolio. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Year 0

	Value				Growth			
	logBE	logME	logBM	logAT	logBE	logME	logBM	logAT
Incomers	0.15	-0.25	0.41	0.14	0.02	0.55	-0.53	0.12
Stock Universe	0.12	0.13	-0.01	0.13	0.12	0.13	-0.01	0.13
Incomers - Stock Universe	0.03**	-0.38***	0.41***	0.01	-0.10***	0.42***	-0.52***	0.00
	(1.96)	(-14.57)	(14.84)	(0.74)	(-9.09)	(21.02)	(-25.27)	(-0.22)
Non-Incomers	0.13	0.13	-0.01	0.13	0.08	0.09	-0.01	0.09
Incomers - Non-Incomers	0.03	-0.39***	0.41***	0.00	-0.06***	0.46***	-0.52***	0.04***
	(1.49)	(-14.09)	(14.14)	(0.27)	(-5.17)	(20.93)	(-25.84)	(4.57)

Panel B: Year 1

	Value				Growth			
	logBE	logME	logBM	logAT	logBE	logME	logBM	logAT
Incomers	0.01	0.12	-0.10	0.05	0.18	0.10	0.08	0.17
Stock Universe	0.11	0.09	0.02	0.12	0.11	0.09	0.02	0.12
Incomers - Stock Universe	-0.09***	0.03	-0.12***	-0.06***	0.07***	0.01	0.06***	0.05***
	(-8.05)	(1.47)	(-5.43)	(-8.75)	(9.68)	(0.60)	(5.39)	(8.13)
Non-Incomers	0.12	0.08	0.03	0.12	0.06	0.09	-0.03	0.08
Incomers - Non-Incomers	-0.10***	0.03	-0.13***	-0.07***	0.11***	0.00	0.11***	0.09***
	(-8.39)	(1.62)	(-5.60)	(-9.74)	(13.54)	(0.22)	(7.22)	(13.08)

Panel C: Year 2

	Value				Growth			
	logBE	logME	logBM	logAT	logBE	logME	logBM	logAT
Incomers	0.00	0.08	-0.08	0.04	0.18	0.03	0.15	0.17
Stock Universe	0.08	0.04	0.04	0.10	0.08	0.04	0.04	0.10
Incomers - Stock Universe	-0.08***	0.04*	-0.12***	-0.06***	0.09***	-0.01	0.11***	0.07***
	(-6.01)	(1.91)	(-5.93)	(-6.48)	(9.95)	(-0.77)	(6.96)	(9.09)
Non-Incomers	0.09	0.04	0.06	0.11	0.05	0.05	-0.01	0.07
Incomers - Non-Incomers	-0.09***	0.04*	-0.13***	-0.07***	0.13***	-0.03	0.16***	0.10***
	(-6.39)	(1.86)	(-5.95)	(-7.13)	(12.26)	(-1.42)	(8.51)	(12.48)

Table 4
Overlaps of Newly Entering HML Stocks with CMA Portfolios

Panel A of this table presents the average excess overlaps of the newly entering value and growth stocks (Incomers) with the contemporaneous, the future (up to three years), and the past (up to three years) CMA portfolios. The portfolios are formed as outlined in Section 2 at the end of each June from 1963 to 2017. An average excess overlap is the average percentage of newly entering value respectively growth stocks that are included in the long leg of the respective CMA portfolio minus the average percentage of value respectively growth stocks that are included in the short leg of the respective CMA portfolio. The percentages are weighted percentages, whereby the weights correspond to the stocks' weights in the respective portfolio at the respective rebalancing date at which they enter the portfolio, scaled to sum to one. The average excess overlaps of the newly entering HML stocks with the CMA portfolios are calculated as the average excess overlaps of the newly entering value stocks with the CMA portfolios minus the average excess overlaps of the newly entering growth portfolio with the CMA portfolios, divided by 2. Moreover, the same results are presented for stocks that could but do not newly enter the value portfolio respectively the growth portfolio (Non-Incomers) at the respective portfolio rebalancing date. The percentages are weighted percentages, whereby the weights correspond to the stocks' market values at the respective rebalancing date. Panel B presents the same results for ME value stocks and ME growth stocks (Incomers (ME)) as well as BE value stocks and BE growth stocks (Incomers (BE)). ME value stocks are those stocks that enter the value portfolio primarily due to a decrease in their market values and ME growth stocks are those stocks that enter the growth portfolio primarily due to an increase in their market values. BE value stocks are those stocks that enter the value portfolio primarily due to an increase in their book values and BE growth stocks are those stocks that enter the growth portfolio primarily due to a decrease in their book values.

Panel A: Incomers and Non-Incomers

Stocks	Year	Value	Growth	HML
	-3	-12.2%	-11.7%	-0.3%
	-2	-13.3%	-7.0%	-3.2%
	-1	-10.6%	-6.1%	-2.3%
Incomers	0	1.6%	-16.7%	9.1%
	1	18.5%	-27.8%	23.2%
	2	17.4%	-18.1%	17.7%
	3	16.4%	-9.6%	13.0%
	-3	-19.1%	-1.6%	-8.7%
	-2	-19.3%	0.4%	-9.9%
	-1	-19.8%	3.0%	-11.4%
Non-Incomers	0	-19.6%	6.0%	-12.8%
	1	-17.0%	7.9%	-12.5%
	2	-11.2%	9.6%	-10.4%
	3	-6.9%	11.4%	-9.1%

Panel B: Incomers (ME) and Incomers (BE)

Stocks	Year	Value	Growth	HML
	-3	-12.4%	-14.5%	1.0%
	-2	-12.6%	-10.5%	-1.0%
	-1	-9.0%	-11.4%	1.2%
Incomers (ME)	0	13.2%	-31.1%	22.1%
	1	20.9%	-37.8%	29.4%
	2	18.9%	-23.3%	21.1%
	3	17.7%	-13.5%	15.6%
	-3	-3.0%	-5.1%	1.1%
	-2	-10.2%	3.2%	-6.7%
	-1	-15.3%	15.3%	-15.3%
Incomers (BE)	0	-56.6%	44.9%	-50.8%
	1	1.7%	20.0%	-9.2%
	2	4.2%	7.0%	-1.4%
	3	6.5%	12.5%	-3.0%

Table 5
HML Returns based on Newly Entering Value and Growth Stocks

Panel A of this table presents for the period from July 1964 to June 2018 the average monthly value return, growth return, and HML return when only i) stocks that newly enter the value and growth portfolios primarily due to changes in their market values (Incomers (ME)), ii) stocks that newly enter the value and growth portfolios (Incomers), and iii) stocks that newly enter the value and growth portfolios primarily due to changes in their book values (Incomers (BE)) are used in the formation of the value and growth portfolios at the end of each June from 1964 to 2017 (see Section 2). For each return, the monthly percent averages (Raw) are displayed. Moreover, for the returns of the cases ii) and iii), the monthly average percent excess returns (Excess) with respect to the corresponding return of case i) are displayed. Panel B of this table presents for the sample period the average monthly value return, growth return, and HML return when only i) stocks that newly enter the value (growth) portfolio primarily due to a decrease (increase) in their market values and that simultaneously neither move into the conservative (aggressive) portfolio nor out of the aggressive (conservative) portfolio (Incomers (ME no-INV)), ii) stocks that newly enter the value (growth) portfolio primarily due to a decrease (increase) in their market values and that simultaneously move into the conservative (aggressive) portfolio and/or out of the aggressive (conservative) portfolio (Incomers (ME INV)), and iii) stocks that newly enter the value (growth) portfolio primarily due to an increase (decrease) in their book values and that simultaneously neither move into the conservative (aggressive) portfolio nor out of the aggressive (conservative) portfolio (Incomers (BE no-INV)) are used in the formation of the value and growth portfolios at the end of each June from 1964 to 2017 (see Section 2). For each return, the monthly percent averages (Raw) are displayed. Moreover, for the returns of the cases ii) and iii), the monthly average percent excess returns (Excess) with respect to the corresponding return of case i) are displayed. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Incomers (ME) and Incomers (BE)

	Value		Growth		HML	
	Raw	Excess	Raw	Excess	Raw	Excess
Incomers (ME)	1.26%***		0.94%***		0.32%**	
	(5.69)		(4.02)		(2.09)	
Incomers	1.21%***	0.04%	0.99%***	-0.05%	0.23%*	0.09%**
	(5.61)	(1.59)	(4.34)	(-1.59)	(1.67)	(2.18)
Incomers (BE)	0.92%***	0.34%**	1.34%***	-0.40%***	-0.43%**	0.74%***
	(3.93)	(2.20)	(5.47)	(-2.73)	(-2.22)	(3.38)

Panel B: Incomers (ME INV), Incomers (ME no-INV), and Incomers (BE no-INV)

	Value		Growth		HML	
	Raw	Excess	Raw	Excess	Raw	Excess
Incomers (ME no-INV)	1.30%***		1.03%***		0.27%*	
	(5.84)		(4.49)		(1.66)	
Incomers (ME INV)	1.21%***	0.09%	0.87%***	0.16%	0.34%**	-0.07%
	(5.21)	(0.84)	(3.51)	(1.43)	(2.01)	(-0.47)
Incomers (BE no-INV)	0.96%***	0.34%**	1.35%***	-0.32%*	-0.40%*	0.66%***
	(3.89)	(1.99)	(5.04)	(-1.76)	(-1.80)	(2.67)

Table 6

HML Returns under Exclusion of Newly Entering Value and Growth Stocks

This table presents for the period from July 1964 to June 2018 the monthly percent averages for the HML return (Raw) when i) all value and growth stocks are used, ii) all conservative stocks are excluded from the value portfolio and all aggressive stocks are excluded from the growth portfolio, iii) only Incomers are used (see Table 5), iv) only Incomers (ME) are used (see Table 5), v) only Incomers (ME INV) are used (see Table 5), vi) only Incomers (ME no-INV) are used (see Table 5), vii) only Incomers (BE) are used (see Table 5), and viii) only Incomers (BE no-INV) are used (see Table 5) in the formation of the value and growth portfolios at the end of each June from 1964 to 2017 (see Section 2). Moreover, the average monthly percent HML returns (New) and their average monthly percent excess returns over the original HML return (Excess) are presented when the stock groups used in the cases ii) - viii) are individually excluded from the formation of the value and growth portfolios. Likewise, the average monthly percent HML returns (New) and their average monthly percent excess returns over the INV-neutral HML return (Excess) are presented when the stock groups used in the cases iii) - viii) are individually excluded from the formation of the value and growth portfolios. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

		Ex from HML		Ex from INV-neutral HML	
	Raw	New	Excess	New	Excess
HML	0.30%***				
	(2.74)				
INV-neutral HML	0.14%	0.45%***	0.15%***		
	(1.43)	(3.18)	(2.64)		
HML Incomers	0.23%*	0.31%***	0.01%	0.12%	-0.01%
	(1.67)	(2.62)	(0.43)	(1.19)	(-0.36)
HML Incomers (ME)	0.32%**	0.28%**	-0.02%	0.08%	-0.05%*
	(2.09)	(2.42)	(-0.79)	(0.83)	(-1.71)
HML Incomers (ME INV)	0.34%**	0.29%***	-0.01%	0.13%	-0.01%
	(2.01)	(2.60)	(-0.68)	(1.35)	(-0.91)
HML Incomers (ME no-INV)	0.27%*	0.29%***	-0.01%	0.10%	-0.04%
	(1.66)	(2.64)	(-0.45)	(0.96)	(-1.58)
HML Incomers (BE)	-0.43%**	0.33%***	0.02%***	0.17%*	0.03%***
	(-2.22)	(2.90)	(3.26)	(1.75)	(3.08)
HML Incomers (BE no-INV)	-0.40%*	0.32%***	0.02%***	0.17%*	0.03%***
	(-1.80)	(2.86)	(2.73)	(1.71)	(2.85)

Table 7
Pricing of HML Returns

This table presents the estimated coefficients from the time-series regressions i) of the standard HML return, ii) of the INV-neutral HML return, iii) of the Incomers HML return, iv) of the Incomers (ME) HML return, v) of the Incomers (ME INV) HML return, vi) of the Incomers (ME no-INV) HML return, vii) of the Incomers (BE) HML return, and viii) of the Incomers (BE no-INV) HML return on an empirical four-factor asset pricing model. Detailed definitions on the formation of the returns are given in Table 5 and Table 6. The four-factor model consists of the market factor (MP), the size factor (SMB), the profitability factor (RMW), and the investment factor (CMA). The construction of the factor returns is described in Section 2 and in the Appendix. Moreover, the estimated intercepts (Int) and the R-squareds from the regressions as well as the returns monthly percent averages (Raw) are displayed. The sample period is from July 1964 to June 2018. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Raw	Int	MP	SMB	RMW	CMA	R-squared
HML	0.30%***	-0.06%	-0.01	0.02	0.26***	1.03***	55.6%
	(2.74)	(-0.74)	(-0.44)	(0.61)	(7.09)	(25.40)	
INV-neutral HML	0.14%	-0.08%	-0.01	0.01	0.21***	0.56***	22.9%
	(1.43)	(-0.85)	(-0.42)	(0.32)	(5.03)	(11.95)	
HML Incomers	0.23%*	-0.03%	-0.02	0.10**	0.11*	0.74***	17.6%
	(1.67)	(-0.20)	(-0.51)	(2.23)	(1.76)	(10.77)	
HML Incomers (ME)	0.32%**	-0.01%	0.00	0.14***	0.09	0.94***	22.7%
	(2.09)	(-0.05)	(-0.06)	(2.91)	(1.39)	(12.79)	
HML Incomers (ME INV)	0.34%**	-0.02%	0.03	0.11**	-0.02	1.17***	27.6%
	(2.01)	(-0.16)	(0.73)	(2.20)	(-0.24)	(14.72)	
HML Incomers (ME no-INV)	0.27%*	-0.01%	-0.03	0.20***	0.22***	0.64***	10.3%
	(1.66)	(-0.07)	(-0.66)	(3.55)	(2.89)	(7.47)	
HML Incomers (BE)	-0.43%**	-0.40%**	-0.16***	0.03	0.29***	-0.11	3.6%
	(-2.22)	(-2.02)	(-3.40)	(0.41)	(3.08)	(-1.06)	
HML Incomers (BE no-INV)	-0.40%*	-0.32%	-0.15***	0.00	0.28**	-0.26**	2.6%
	(-1.80)	(-1.42)	(-2.68)	(0.03)	(2.54)	(-2.18)	

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