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Pricing, issuance volume, and design of innovative securities: The role of investor information[☆]

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ABSTRACT

This study investigates the role of asymmetric information for the pricing, issuance volume, and design of innovative securities. By analyzing the information that structured product issuers provide to the investors of those products, we can identify specific sources of asymmetric information between the issuers and investors in this market. We show that issuers exploit this information friction to offer products to investors that appear more profitable for the issuer. In addition, we find that the friction induces issuers to design products with higher information asymmetry. Our results suggest that product issuers' behavior increases information frictions in the financial system.

1. Introduction

Retail investors make investment mistakes in the innovative securities market that lead to large welfare costs (Shiller, 2003). Recent empirical studies and anecdotal evidence from lawsuits suggest that asymmetric information between financial institutions and retail investors is a primary explanation for these mistakes (e.g., Zingales, 2015; Egan, 2019). Information frictions in the innovative securities market have attracted particular attention after the 2008–2009 financial crisis because of concerns that they can cause dramatic market disruptions (Gennaioli et al., 2012; Hanson and Sunderam, 2013). Thus, asymmetric information is a key concern from both a consumer protection and financial stability perspective. Research in this field, however, typically faces the challenge that market participants' information sets are not observable.

This study investigates the influence of asymmetric information on the financial innovation market. We overcome the challenge of observing information sets through our access to a novel structured product database in Switzerland. This database represents an ideal laboratory to explore the role of asymmetric information in the financial innovation market because it contains the information that product issuers provide to investors. The advantage of using Swiss data is that 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 identify the information gap between investors and product issuers. In addition, structured products in Switzerland are frequently issued to retail investors (SSPA, Swiss Structured Products Association, 2013), who usually have inferior information compared to that held by financial intermediaries (Bhattacharya et al., 2012). Our analysis provides three main results. First, asymmetric information plays a key role in explaining the markups of structured products. Second, issuance volumes are larger when information asymmetry is higher. Third, issuers design products toward asymmetric information.

The market for structured products is well established in Europe and has grown substantially in the US in recent years (Henderson et al., 2020; Bouveret et al., 2013). Thus, structured products represent an important segment of the market for innovative securities. Our database contains term sheets of all structured products on single-stock underlyings issued in Switzerland. These term sheets summarize the important product characteristics for the investors.

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Before describing our analysis in detail, we discuss why product issuers are differently informed about their structured products than retail investors and how we identify this information asymmetry. Issuers are obliged to disclose important product information to investors on the term sheets. By analyzing the information content of these term sheets, we find that the missing pieces of information needed to assess the replication price of structured products are the volatility and dividends of the products' underlyings. The financial institutions that issue the products have an information advantage on these parameters because they can access the implied volatilities and forecasted dividends from databases such as BLOOMBERG and IBES. As the databases are disproportionately costly to retail investors, this information access friction causes information asymmetry between product issuers and retail investors.

We start by calculating 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 the issuers' gross product margin. Analyzing price differences helps isolate the impact of information asymmetry on $Markups$ because price determinants not associated with market frictions usually affect both the issue and replication prices, but not their difference.

We first investigate whether issuers charge higher $Markups$ when this information asymmetry induces investors to overvalue a certain product. Specifically, the replication prices in our sample decline with volatility or dividends. Thus, investors overestimate a product's value when they underestimate volatility or dividends. We proxy for investors' tendency to underestimate the pricing-relevant volatility or dividend with dummies that capture whether the implied volatility is higher than the historical volatility or the forecasted dividend is higher than the historical dividend. The idea behind this approach is based on the observation that retail investors commonly refer to publicly available historical information (Daniel et al., 2002; Sirri and Tufano, 1998). Thus, we incorporate that investors use historical proxies for the missing, pricing-relevant information on volatility and dividends. We find that issuers earn a 73% (108 basis points) larger $Markup$ with products for which the underlying's implied volatility is higher than its historical volatility. Similarly, they earn a 29% (43 basis points) higher $Markup$ with product on underlyings for which analysts forecast a higher dividend than the historical dividend. These results suggest that issuers exploit information asymmetry by increasing product $Markup$ when this information friction induces retail investors to overestimate a structured product's value.

We apply a battery of tests to confirm this information hypothesis and to exclude alternative explanations for our results. For example, the relation between $Markup$ and products with a higher implied than historical volatility reverses in a secondary sample of products for which the replication prices increase with volatility and, thus, a higher historical than implied volatility induces investors to overvalue the products. This result is difficult to reconcile with alternative explanations for our findings. We also show that issuers' tendencies to exploit the information channel is stronger when the issuers' information is more accurate, products are more complex, and market uncertainty is higher.

Next, we analyze the influence of information asymmetry on the issuance volume of structured products. To this end, we exploit an exogenous information shock. Specifically, whereas access to analyst forecasts gives issuers a dividend information advantage over investors, this advantage vanishes once the dividend of a product's underlying is publicly announced. We find that such dividend information shocks reduce the issuance volume of products that investors tend to overvalue due to dividend information asymmetry. This effect is substantial. Specifically, our results imply that the issuance volume of overvalued products drops by 29% once the shock mitigates the dividend information asymmetry. The use of dividend announcements as information shocks has two key advantages. First, product issuers cannot influence dividend announcement dates, which mitigates endogeneity concerns. Second, it is unlikely that dividend announcements alter investors' financial sophistication levels. Thus, the observation that a dividend information shock, which is unrelated to a sophistication shock, mitigates investment mistakes is crucial to the regulatory debate around investors' lack of financial sophistication to understand structured products (e.g., Henderson and Pearson, 2011). Specifically, our results call for disclosure, whereas addressing the lack of financial sophistication would evoke more comprehensive regulatory measures such as the expansion of financial education or product-selling restrictions.

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

The information asymmetry hypotheses we postulate only impose 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 of the same product category reduces issuers' opportunities to exploit investors. However, the simple comparison argument holds only for the product terms disclosed on a term sheet. Thus, our asymmetric 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 model-free rank ordering along these dimensions. Campbell (2006) highlights that many households find solutions to relatively complex investment problems. Thus, it is 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 three streams of the literature. The first stream analyzes the reasons behind investors' mistakes in the market for innovative securities (DeMarzo, 2005; Coval et al., 2009; Choi et al., 2009; Carlin, 2009; Carlin and Manso, 2011; Henderson and Pearson, 2011; Célérier and Vallée, 2017; Chang et al., 2015; Zingales, 2015; Egan, 2019). This literature argues that financial intermediaries' tendency to dupe unsophisticated investors by excessively selling them innovative securities with high markups is a crucial concern from an investor protection perspective. 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 why investors buy products with high markups. Given the high markups and, thus, the poor performance of structured products, retail investors' high demand for these products is puzzling (Henderson and Pearson, 2011; Vokata, 2021). We contribute to this literature by identifying information asymmetry as an important additional explanation for the high markups and excess product issuance in the market for innovative securities. Thus, we 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).

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

Second, we add to the literature that points to asymmetric information as a crucial friction in the market for innovative securities (Ashcraft and Schuermann, 2008; An et al., 2011). Gorton and Metrick (2012), Stein (2012), and Hanson and Sunderam (2013) argue that information frictions are risky for the entire financial system because they can cause large market disruptions when new information arrives. Gennaioli et al. (2012) show that investors' excessive demand for innovative securities that contain neglected risks, coupled with the intermediaries' tendency to profitably serve this demand by overissuing these securities, can lead to financial market fragility and large welfare losses. Despite this systemic risk concern, surprisingly little is known about the sources of asymmetric information in the market for innovative securities. One exception is the mortgage market, in which the underlying asset quality and neighborhood characteristics are key drivers of information frictions (Piskorski et al., 2015; Kurlat and Stroebel, 2015; Stroebel, 2016). We contribute to addressing the systemic risk concern due to information frictions along three dimensions. First, we identify volatility and dividends as two important sources of the investor information friction in the market for innovative securities. Second, we show that disclosure reduces issuers' issuance volume for products that investors tend to overvalue due to information asymmetry. Third, our results pertaining to the design of structured products emphasize the systemic stability concerns. Specifically, they show that financial innovators deliberately structure products for which investors have inferior information, thereby underpinning the concern that financial engineering aggravates investor information frictions in the market for innovative securities.

Finally, this study contributes to the literature on drivers of security design. The traditional view of financial innovation is that financial institutions design innovative securities to complete markets or mitigate financial frictions (Allen and Gale, 1988; Duffie and Rahi, 1995; Ross, 1989). More recent literature highlights the fact that issuers also tailor these securities to exploit investors by obfuscating risk or catering to behavioral biases (Carlin, 2009; Célérier and Vallée, 2017; Gabaix and Laibson, 2006; Li et al., 2018). Our results suggest that the exploitation of information frictions is an additional important driver of the design of innovative securities.

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.

Structured products are an important asset class. Bouveret et al. (2013) report that the notional volume invested in structured products amounts to 4% of household financial wealth or 12% of mutual funds' assets under management in the European market. As of December 2020, the total outstanding volume of retail structured products in the European Union was 400bn EUR (ESMA, 2022). With an outstanding volume of 220bn EUR at the end of 2021, Switzerland is the largest European issuer of structured products (European Structured Investment Products Association, 2021). The typical average maturity of structured products is around one year (Wallmeier and Diethelm, 2009; Vokata, 2021). Thus, the outstanding volume approximately equals the yearly issuance volume. While the US structured products market has traditionally lagged behind its European counterpart, it has 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. The global outstanding volume (retail and non-retail segment) of structured products was estimated at 7tn USD in 2019.[2] 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. (2022), a typical retail structured product investor is 55 years old, has an above-average education, exhibits an above-average disposable income, and possesses above-average financial wealth.

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 asymmetric 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 structured product issuers must provide to investors in detail (Swiss Bankers Association, 2007). For example, all term sheets must disclose the product's strike price, maturity, and payment details such as the coupon payments. The information on the term sheets is highly standardized, which allows us to define proxies of asymmetric 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. Finally, the database features a large number of relatively simple structured products, which makes it easy for investors to compare products along the dimensions provided on the term sheets. This comparability reduces the concern that investors lack the financial sophistication to incorporate volatility and dividend dimensions for their product selection decision even if this information was provided on term sheets.

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 four 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 two weeks typically until a few days before the initial fixing date. 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.[3] Investors receive the final 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 15'291 publicly issued products that target the retail market. Our analysis requires the calculation of the markup 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. Thus, we exclude the 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.[4] We also

[2] see https://www.bloomberg.com/professional/blog/sure-time-to-grasp-the-potential-of-structured-products/ (last accessed on December 13, 2021.)

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

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

omit index products (947) because their underlying lacks the discrete dividend payment structure that we explore in our product sample on single equity underlyings. Thus, we can neither define our main explanatory dividend dummy nor conduct our dividend information shock analysis on index products.[5] Finally, we omit 20 products due to missing data. These criterions leave us with 1'133 products on single equity underlyings. Most of these remaining products feature both a positive Delta and a negative Vega, i.e., their values are positively related to the underlying's price and negatively related to the underlying's volatility. We consider the 1'012 products with a positive Delta and a negative Vega as our main sample for the primary analysis. 107 products feature a positive Vega. We present a separate analysis for this secondary sample because a positive Vega implies opposing results according to our information hypothesis. Finally, we omit the 14 products with a negative Delta as this number of observations is insufficient to conduct a separate analysis.

We manually collect the terms of the 1'119 products in our two samples 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. (2021) extract 501 products from the same structured products database.[6]

Table 1 reports the number of products in our main sample grouped by issuer, product category, year, and most frequently used underlyings. 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. Except for the Bonus Certificates, all products in our sample are so-called yield enhancement products (YEPs). YEPs represent the largest retail structured product class in terms of number of offered products in the US and in terms of outstanding volume in Europe (Vokata, 2021; European Structured Investment Products Association, 2021). Thus, our product types are representative of the European and US market.

We now describe the product categories in our main sample of positive Delta and negative Vega products. Fig. 1 depicts the payoff profile of each product category in this sample.

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 (final fixing date), 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.

Table 1
Overview of structured products sample.

	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
Total	**1012**
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
Total	**1012**
Panel C: By Year	
2005	73
2006	165
2007	249
2008	272
2009	178
2010	75
Total	**1012**
Panel D: Most Frequent Underlyings	
Nestle	85
Credit Suisse	69
ABB	60
Novartis	59
Roche	49
Swiss Re	47

This table presents the number of structured products of the main sample grouped by issuer, product category, year, and underlying. The product categories are described in Section 2. 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.

[5] We can, however, test the relation between our main explanatory volatility dummy $Higher\ Volatility$ that captures whether the implied volatility is higher than the historical volatility and $Markups$ for index products. For comparability, we restrict the index products analysis to the product categories of our main sample (418 products). We also drop products with missing information and without traded EUREX options (299), which leaves us with 119 products from three product categories. We use continuous dividend yields from Datastream to calculate the replication prices of index products. Table A.2 in the Appendix shows that $Higher\ Volatility$ is significantly positive for index products, which confirms the result of our main sample.

[6] Vokata (2021) 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.

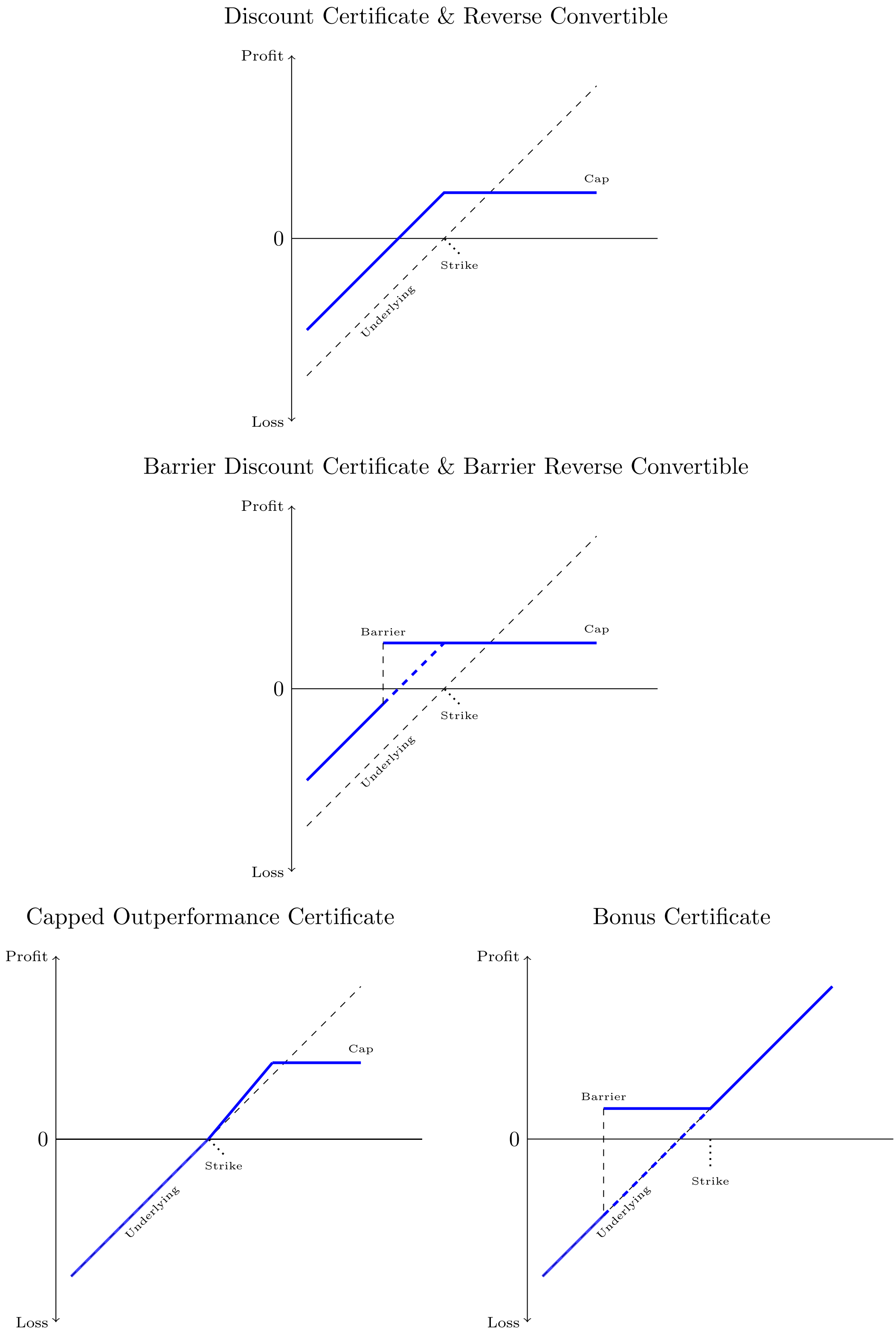


Fig. 1. Payoff profiles.
This figure illustrates the payoff profiles of the product categories in our sample. Each graph depicts the payoff in the nominal currency of the product with respect to the product's underlying reference price at its final fixing date.

3. Asymmetric information and product markups

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

3.1. Product markups

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.[7] The $Markup$ is the percentage difference between the $Issue\ Price$ and the $Replication\ Price$. Therefore, $Markup$ measures a product's percentage gross margin 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.[8]

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 the main sample is 1.48%. This magnitude coincides with the average markups 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. The average yearly issuance volume of the products in our sample is 1.14bn CHF. The total yearly issuance volume of yield enhancement products (YEPs) to retail investors in Switzerland during our sample period is around 19bn CHF.[9] Thus, our sample represents around 6% of the total yearly issuance volume of YEPs to retail investors in Switzerland.

[7] 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.

[8] 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 $Markup$.

[9] https://data.snb.ch/en/topics/banken/cube/bawebesecja

3.2. Asymmetric information: Volatility and dividends

The literature suggests that issuers can overprice structured products as they are free to choose contract terms that differ from comparable products of competitors (Carlin, 2009; Henderson and Pearson, 2011; Li et al., 2018). This differentiation implies that products are not homogeneous. Thus, imperfect price competition allows issuers to earn markups in this market.

Our asymmetric 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 within a product category by comparing the products' key terms even if the investors lack the ability to actually price these products.[10] 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 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 dimensions underlying risk or dividend if they have that information.

To investigate whether asymmetric information affects $Markups$, we first analyze the information content of product term sheets. To this end, we inspect the obligatory information items listed in the Swiss Bankers Association (2007) guidelines. Table 3 presents an overview of all the obligatory information items the Swiss regulator requires issuers to disclose on the term sheets. We find that the only two missing items necessary to calculate (or compare) the products' replication prices (that are not publicly available) are the implied volatility of the underlying and expected dividend.[11,12] 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. Structured product issuers have access to these parameters through standard information systems such as BLOOMBERG. As these systems are very costly[13], retail investors typically lack the possibility to retrieve implied volatility and expected dividend information. Thus, the missing volatility and dividend information on the term sheets causes an information friction that induces asymmetric information.

Our first hypothesis is that issuers charge higher $Markups$ when information asymmetry regarding volatility induces investors to overvalue a certain product. For the main analysis, we proxy for investors'

[10] 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.

[11] 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 .

[12] 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://data.snb.ch/en/topics/ziredev#!/cube/zimoma, last accessed on December 08, 2021.). In addition, most term sheets contain an indication of the interest rate.

[13] One year of access to BLOOMBERG's system, for example, costs around 25'000 USD per user (Ben-Rephael et al., 2017).

Table 2
Descriptive statistics.

Dependent variables	Mean	Std. Dev.	Q10	Median	Q90
Markup (in %)	1.48	2.09	−0.65	1.35	3.87
Issuance Volume	15.73	1.02	14.20	15.84	17.09
Explanatory Variables	Mean	Std. Dev.	Q10	Median	Q90
Implied Volatility (in %)	28.67	11.26	16.70	26.18	43.18
Historical Volatility (in %)	31.24	18.59	15.33	24.40	60.26
Higher Volatility	0.56	0.50	0	1	1
Volatility Difference (in %)	−2.57	11.68	−15.95	0.75	6.52
Forecasted Dividend (in %)	2.73	2.18	0.00	2.51	5.88
Historical Dividend (in %)	3.83	6.33	0.00	2.31	6.77
Higher Dividend	0.60	0.49	0	1	1
Dividend Difference (in %)	−1.11	6.21	−3.70	0.20	1.94
Market Cap	3.80	1.09	2.03	4.08	4.97
3 m Excess Return (in %)	1.46	11.09	−11.87	1.35	14.47
12 m Excess Return (in %)	0.87	21.26	−23.29	0.18	30.99
1 m Turnover	7.45	1.92	4.31	8.21	9.37
3 m Turnover	8.55	1.91	5.59	9.27	10.47
1 m Call Option Volume (in %)	2.63	3.79	0.08	1.66	5.70
1 m Put Option Volume (in %)	2.55	3.41	0.07	1.66	5.61
Vega	−0.46	0.29	−0.57	−0.44	−0.21
Delta	1.54	1.84	0.19	0.95	3.46
IBES Coverage	15.29	12.09	1	17	30
Swiss Stock	0.63	0.48	0	1	1
Complexity	2.50	0.50	2	2	3
Implied Volatility 182 (in %)	31.19	14.73	16.04	28.32	48.68
Time to Maturity (trading days)	294.16	127.67	249	255	542.09

This table presents descriptive statistics of the main sample containing structured products issued in Switzerland between January 2005 and December 2010 on a single equity underlying with a negative $Vega$. The main sample consists of 1012 products. $Markup$ is the issue price of a structured product minus its replication price, scaled by the issue price, expressed in percentage points. We calculate $Issuance\ Volume$ as the natural logarithm of a structured product's issuance volume (in USD). $Implied\ Volatility$ is the annualized implied volatility of the product's option on the underlying calculated for the lifetime of the product. We calculate $Historical\ Volatility$ as the standard deviation of a product underlying's returns over the 255 trading days before the initial fixing date. $Higher\ Volatility$ is a binary variable that is equal to one if $Implied\ Volatility$ is larger than $Historical\ Volatility$ and zero otherwise. $Volatility\ Difference$ is the difference between $Implied\ Volatility$ and $Historical\ Volatility$. $Forecasted\ Dividend$ 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 $Historical\ Dividend$ 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. $Higher\ Dividend$ is a binary variable that is equal to one if $Forecasted\ Dividend$ is larger than $Historical\ Dividend$ and zero otherwise. $Dividend\ Difference$ is defined as the difference between $Forecasted\ Dividend$ and $Historical\ Dividend$. $Market\ Cap$ 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. $Vega$ ($Delta$) is a product's annualized Vega (Delta) scaled by the product's initial value. $IBES\ Coverage$ is the number of IBES analysts that forecast the next dividend for an underlying at the initial fixing date. $Complexity$ is defined as the number of features embedded in a product based on the methodology of Célérier and Vallée (2017). $Swiss\ Stock$ is a dummy that is equal to one if a product's underlying is a Swiss stock and zero otherwise. We calculate $Implied\ Volatility$ 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 trading days between the initial fixing date and the maturity date of a structured product.

tendency to overvalue a structured product due to volatility information asymmetry with the simple $Higher\ Volatility$ dummy. This dummy is equal to one if the implied volatility ($Implied\ Volatility$) of a product's underlying is larger than its historical volatility ($Historical\ Volatility$). 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 overvaluation due to information asymmetry on $Markups$. We also consider the continuous differences between $Implied\ Volatility$ and $Historical\ Volatility$ as an alternative proxy and obtain similar results.

The intuition behind the $Higher\ Volatility$ proxy starts from the observation that the replication prices of all products in our main sample decline with the implied volatility of 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.[14] Thus, investors tend to overvalue a structured product if $Implied\ Volatility$ is larger than $Historical\ Volatility$. In this case, investors underestimate volatility based on their available historical information, and hence overestimate a product's replication price.

Our second hypothesis is that issuers charge higher $Markups$ when information asymmetry regarding dividends induces investors to overvalue a certain product. We proxy for investors' tendency to overvalue a structured product due to dividend information asymmetry with the simple $Higher\ Dividend$ dummy. This dummy is equal to one if the dividend forecast ($Forecasted\ Dividend$) of a product's underlying is larger than its historical dividend ($Historical\ Dividend$). We also show that our results are robust to using the continuous differences between $Forecasted\ Dividend$ and $Historical\ Dividend$ as alternative proxies.

The intuition behind the $Higher\ Dividend$ proxy is analogous to that of the $Higher\ Volatility$ proxy. Specifically, structured product investors are not entitled to receive dividend payments because they

[14] In Fig. 2, we extract a typical picture of the underlying's historical price evolution as provided in a product term sheet from our sample.

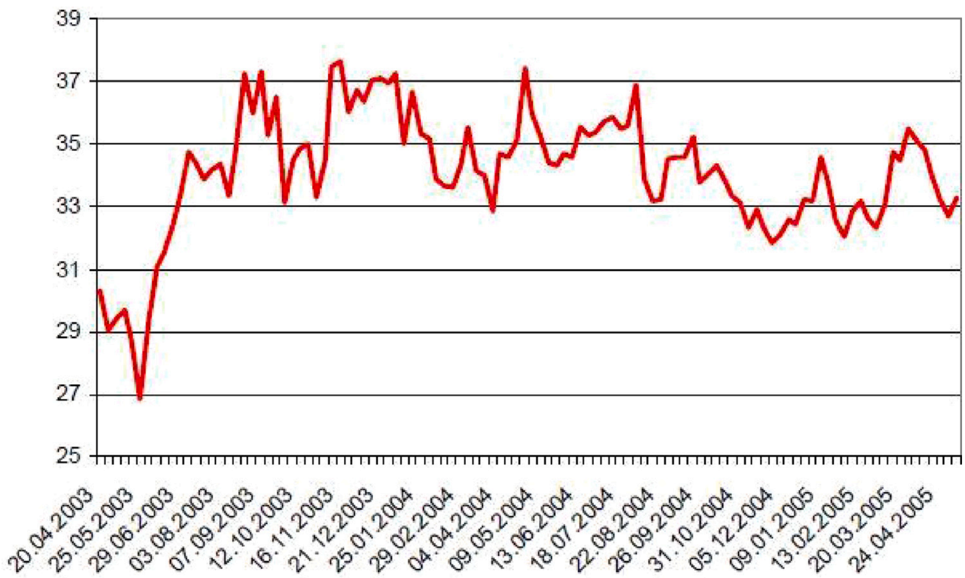


Fig. 2. Historical price evolution.
This figure depicts an excerpt of a product term sheet in our sample that shows the historical price evolution of the BMW AG share over the years before issuance.

Table 3
Term sheet information.

- Name
- Head office
- Guarantor (if applicable)
- Brief description of the type of product
- Swiss securitiy number and ISIN
- Calculation agent
- Total amount and minimum investment
- Currency of the security
- Issue price
- Trading volume and ratio
- Rights attached to the security
- Seniority/subordination (if any)
- Exercise detail, exercise style
- Maturity/point in time
- Price-setting, payment, expiration and redemption details
- Paying agent, exercise agent
- Indication that the security is not listed
- Restriction on transferability, tradability, trading details
- Redemption details
- Fees imposed on the purchaser during the term of the investment after issue (e.g. management fees for tracker certificates)
- Reference to tax treatment in Switzerland
- Product-specific risks
- Issuer risk
- Description of the underlying value or values or how they are calculated
- Identification of the underlying value (Swiss security number, ISIN)
- Reference to the relevant exchange or index calculation agent

This list contains all the information that structured product issuers must provide on the termsheets based on the guidelines imposed by the Swiss regulator (Swiss Bankers Association, 2007).

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.[15] Thus, investors tend to overvalue a structured product if $Forecasted\ Dividend$ is larger than $Historical\ Dividend$. 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. $Implied\ Volatility$ 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 Appendix. $Historical\ Volatility$ 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.[16] Table 2 shows that the average implied and historical volatilities are 28.67% and 31.24%, respectively. For 563 of the 1'012 products in our main sample the $Higher\ Volatility$ dummy is one.

$Forecasted\ Dividend$ 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. $Historical\ Dividend$ 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. $Forecasted\ Dividend$ and $Historical\ Dividend$ 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 main sample, $Higher\ Dividend$ is one. The underlyings of 12 products in the main sample never pay a dividend and always carry a $Forecasted\ Dividend$ of zero during our sample period. The $Higher\ Dividend$ dummy of these products is zero. The correlation between $Higher\ Volatility$ and $Higher\ Dividend$ is 0.08.

3.3. Empirical approach and identification

To investigate the impact of asymmetric information on product $Markups$, we run cross-sectional OLS regressions of $Markups$ on our

[15] For example, on finance.yahoo.com.

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

explanatory and control variables. Our regression model is

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

where $Markup_i$ is the $Markup$ of product i. $Higher\ Dummy_i$ represents our proxy for investors' overvaluation due to information asymmetry, which are the $Higher\ Volatility$ dummy for volatility and the $Higher\ Dividend$ dummy for dividends. Hence, $Higher\ Dummy_i$ represent our primary explanatory variables.

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, and exploiting cross-sectional variation in our data to show that the effect of the explanatory variables is stronger when the information channel is more plausible.

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 ($Excess Return$, $Market\ Cap$, 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.[17] In addition, we include product category fixed effects to control for heterogeneity across product categories. For example, Célérier and Vallée (2017) show that more complex product categories tend to exhibit a higher markup. In a further specification, we control for issuer fixed effects and underlying fixed effects. In Section 6, we incorporate additional control variables for competition, issuers' default risk, funding needs, the economic environment, and a products' time to maturity. 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 test interaction terms with variables that we include in Table 2.

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

3.4. Results on markups and asymmetric information

We start by investigating the impact of asymmetric volatility information on $Markup$s in our main sample ((1)–(6)). In Column (1) of Table 4, we first estimate the regression model (2) with $Higher\ Volatility$ as a proxy for investors' overvaluation due to information asymmetry. The coefficient of $Higher\ Volatility$ implies that issuers demand a 1.077% 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 increase products' $Markups$ when investors tend to overvalue products due to volatility information asymmetry; that is, when retail investors underestimate volatility based on their historical information. Overall, the control variables are in line with the results in Henderson and Pearson (2011), $Implied\ Volatility$ is significantly positively associated with $Markup$s in our main sample and the remaining controls are mostly insignificant or not robust (see Columns (1)–(7)).

We address the concern that $Higher\ Volatility$ could simply identify a (potentially non-linear) dimension of $Implied\ Volatility$ in two ways. First, we show in Section 6 that the coefficient on $Higher\ Volatility$ is robust to using $Implied\ Volatility\ Squared$ as an additional control. Second, we calculate the average $Implied\ Volatility$ of products with a $Higher\ Volatility$ dummy of one. Their average $Implied\ Volatility$ (26.527%) is significantly smaller than that of products with a $Higher\ Volatility$ dummy of zero (31.353%), with a t-statistics of 6.93 using a two-sample t-test. Thus, products with a $Higher\ Volatility$ dummy of one carry a larger markup that cannot be explained by a higher implied volatility.

Next, we test whether product issuers also exploit dividend information asymmetry. To this end, we incorporate our proxy for investors' tendency to overvalue products due to dividend information asymmetry in Column (2). Products with $Higher\ Dividend$ equal to one carry an $Markup$ that is, on average, 0.430% higher than that for products with $Higher\ Dividend$ equal to zero. The effect is economically important because it corresponds to an increase of almost 30% of the average $Markup$. In addition, the coefficient and statistical significance of $Higher\ Volatility$ remain unchanged. This result provides a first confirmation of our second hypothesis that issuers collect higher $Markup$s when investors overvalue a product due to information asymmetry.

Our estimations suggest that information asymmetry is not only statistically but also economically important for several reasons. First, both information friction dummies explain a significant part of the variation in $Markup$. Specifically, the exclusion of $Higher\ Volatility$ and $Higher\ Dividend$ from the regression model in Column (2) would reduce R^2 by five percentage points, which corresponds to a relative reduction of R^2 by almost 18% (not tabulated). In addition, besides the product category fixed effects and $Implied\ Volatility$, the coefficients of $Higher\ Volatility$ and $Higher\ Dividend$ exhibit the highest explanatory power as measured by the partial ω^2 (not tabulated). Second, the economic magnitudes of investors' overvaluation due to volatility and dividend information asymmetry on $Markup$ are 107 and 43 basis points, respectively. These magnitudes are comparable to that of alternative prominent influence factors discussed in the literature. For example, Célérier and Vallée (2017) show that going from the least to the most complex product category increases $Markup$s by, on average, 136 basis points. Egan (2019) estimates that brokers' misaligned incentives and investors' search frictions in the structured products market reduce the investors' performance by up to 120 basis points per product. Further, the additional $Markup$ due to information asymmetry is comparable to the total $Markup$ charged by financial institutions for alternative products. For example, the average fee for equity mutual funds is 100 bps, and the average fees across funds (mutual funds, hedge funds, private equity funds, and venture capital funds) are between 110 and 160 bps (Greenwood and Scharfstein, 2013). Third, our estimations suggest that information asymmetry exploitation

Table 4
OLS regressions of markups on information measures.

Variables	(1) Markup (in %)	(2) Markup (in %)	(3) Markup (in %)	(4) Markup (in %)	(5) Markup (in %)	(6) Markup (in %)	(7) Markup (in %)
Higher Volatility	1.077***	1.073***				0.966***	−1.633*
	(6.18)	(6.20)				(5.21)	(−1.70)
Implied Volatility	0.042***	0.049***	0.043***	0.055***	0.046***	0.064***	−0.070
	(3.56)	(4.50)	(5.34)	(4.72)	(5.72)	(4.41)	(−0.73)
Higher Dividend		0.430***				0.387**	0.417
		(2.65)				(2.28)	(0.54)
Forecasted Dividend		0.033	0.016	0.037	0.007	0.059	0.005***
		(0.70)	(0.37)	(0.79)	(0.17)	(1.08)	(6.14)
Volatility Difference			0.072***		0.073***		
			(5.96)		(6.01)		
Dividend Difference				0.022**	0.026***		
				(2.33)	(2.99)		
Market Cap	−0.091	−0.130	−0.113	−0.049	−0.103	0.432	0.214
	(−0.93)	(−1.29)	(−1.07)	(−0.45)	(−0.97)	(0.86)	(0.50)
3 m Excess Return	1.019	1.047	1.504*	0.560	1.388	0.803	−7.029**
	(1.15)	(1.23)	(1.70)	(0.58)	(1.58)	(0.86)	(−2.76)
12 m Excess Return	−0.121	−0.097	−0.307	−0.130	−0.362	−0.495	−0.763
	(−0.31)	(−0.26)	(−0.80)	(−0.31)	(−0.93)	(−1.17)	(−0.57)
1 m Turnover	−0.137	−0.115	−0.078	0.190	−0.081	0.118	0.013
	(−0.42)	(−0.36)	(−0.25)	(0.59)	(−0.26)	(0.34)	(1.27)
3 m Turnover	0.177	0.161	0.122	−0.161	0.125	−0.371	−0.012
	(0.58)	(0.53)	(0.42)	(−0.52)	(0.43)	(−0.72)	(−1.14)
1 m Call Option Volume	1.563	2.316	2.513	0.424	2.520	0.049	0.064
	(0.57)	(0.98)	(0.97)	(0.14)	(0.97)	(0.02)	(1.11)
1 m Put Option Volume	−0.761	−1.912	−1.268	−0.501	−1.552	1.624	−0.117
	(−0.23)	(−0.66)	(−0.34)	(−0.15)	(−0.42)	(0.40)	(−0.99)
Issuance Volume	0.162**	0.149*	0.116	0.224**	0.123	−0.430***	0.162
	(2.03)	(1.87)	(1.47)	(2.70)	(1.58)	(−4.87)	(0.65)
Constant	−3.336**	−3.533**	−1.900	−3.717**	−2.213	7.988**	−6.841
	(−2.20)	(−2.39)	(−1.33)	(−2.45)	(−1.57)	(2.52)	(−0.82)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product Category FE	Yes	Yes	Yes	Yes	Yes	No	Yes
Underlying FE	No	No	No	No	No	Yes	No
Issuer FE	No	No	No	No	No	Yes	No
Observations	1012	1012	1012	1012	1012	1012	104
R-squared	0.279	0.290	0.306	0.242	0.311	0.414	0.585

This table presents the results of OLS regressions. In Columns (1)–(6), we use the main sample. In Column (7), we repeat the analysis for the secondary sample. 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. $Implied\ Volatility$ is the annualized implied volatility of the product's option on the underlying calculated for the lifetime of the product. We calculate $Historical\ Volatility$ as the standard deviation of a product underlying's returns over the 255 trading days before the initial fixing date. $Higher\ Volatility$ is a binary variable that is equal to one if $Implied\ Volatility$ is larger than $Historical\ Volatility$ and zero otherwise. $Forecasted\ Dividend$ 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 $Historical\ Dividend$ 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. $Higher\ Dividend$ is a binary variable that is equal to one if $Forecasted\ Dividend$ is larger than $Historical\ Dividend$ and zero otherwise. $Volatility\ Difference$ is the difference between $Implied\ Volatility$ and $Historical\ Volatility$. $Dividend\ Difference$ is defined as the difference between $Forecasted\ Dividend$ and $Historical\ Dividend$. The standard controls are defined in Table 2. We control for year fixed effects and product category fixed effects. Depending on the specification of the regression, we additionally control for issuer and underlying fixed effects. The standard errors are clustered at the underlying level. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

is an important source of income for issuers. In particular, the coefficients imply that issuers' additional yearly income from exploiting the volatility and dividend information asymmetry in the Swiss structured products market is around 1.1bn USD and 0.5bn USD, respectively.[18]

We also investigate whether the estimated quantitative magnitude of our information friction proxies is consistent with our information exploitation hypothesis. To this end, we first approximate the average extent to which investors overvalue $Higher\ Volatility$ and $Higher\ Dividend$ products due to information asymmetry and then compare this value to the size of the coefficients. Information exploitation implies that the $Higher\ Volatility$ and the $Higher\ Dividend$ coefficients should be an economically significant portion of this overvaluation but still lie below 100% of the overvaluation. Otherwise, alternative explanations must drive the coefficient. To approximate the extent to which investors overvalue $Higher\ Volatility$ and $Higher\ Dividend$ products, we compute the difference between $Implied\ Volatility$ ($Forecasted\ Dividend$) and $Historical\ Volatility$ ($Historical\ Dividend$) of each product with a $Higher\ Volatility$ ($Higher\ Dividend$) dummy equal to one and multiply each difference with the product's absolute $Vega$ ($Delta$). Intuitively, the resulting values are an investor's percentage product misvaluation if he or she would completely rely on historical rather than forward-looking information. The average of the vega-adjusted misvaluation between $Implied\ Volatility$ and $Historical\ Volatility$ is 1.900%. Thus, the coefficient of $Higher\ Volatility$ in

[18] In our sample, the share of products with $Higher\ Volatility = 1$ ($Higher\ Dividend = 1$) is 55.63% (60.08%) and the estimated additional $Markup$ is 1.073% (0.430%). If these shares and additional $Markups$ are representative of the entire Swiss structured products market, the estimated additional income for 2020, for which the approximate issuance volume in the Swiss structured products market was 186bn USD, equals 186bn·55.63%·1.073% = 1.1bn USD (186bn·60.08%·0.430% = 0.5bn USD).

Column (2) suggests that issuers are, on average, able to exploit approximately 56.474% (1.073% of 1.900%) of investors' overvaluation due to volatility information asymmetry. The average of the delta-adjusted misvaluation between $Forecasted\ Dividend$ and $Historical\ Dividend$ equals 1.497%. Based on the estimated coefficient of $Higher\ Dividend$ in Column (2), issuers are, on average, able to exploit 28.724% (0.430% of 1.497%) of investors' overvaluation due to dividend information asymmetry.[19] Both values are in the plausible range.

A potential limitation of using the dummy variables $Higher\ Volatility$ and $Higher\ Dividend$ is that they may just capture non-linear effects for products with high $Implied\ Volatility$ and high $Forecasted\ Dividend$, respectively. To address this concern, we replace our explanatory dummies with continuous variables. $Volatility\ Difference$ is the difference between $Implied\ Volatility$ and $Historical\ Volatility$. $Dividend\ Difference$ is the difference between $Forecasted\ Dividend$ and $Historical\ Dividend$. The results are presented in Columns (3)–(5) of Table 4. The coefficients of both variables are positive and significant. Thus, a higher product overvaluation of investors due to information asymmetry entails a higher $Markup$.

Another concern with our results is a potential correlation of unobserved heterogeneity at the underlying or issuer level with at least one of the main explanatory variables. Thus, we rerun the regressions with underlying and issuer fixed effects.[20] Our results are robust to this alternative specification, as shown in Column (6) of Table 4.

A potential caveat with our volatility information friction proxy is that $Higher\ Volatility$ may capture a dimension of underlying uncertainty, which could, for example, affect an issuer's expected hedging or structuring costs. Thus, issuers may simply demand a larger $Markups$ for products with a $Higher\ Volatility$ dummy equal to one to cover these products' higher structuring and hedging costs. Our database allows us to address this concern by disentangling the alternative underlying uncertainty explanation from our information exploitation hypothesis. Specifically, it also contains products for which the products' replication values increase with the implied volatility of their underlyings (positive $Vega$). For these products, retail investors actually tend to underestimate a product's replication price if $Higher\ Volatility$ is equal to one because they tend to underestimate volatility based on their available historical information. Hence, if $Higher\ Vola$ on these products is equal to one, the underlying of these products may still be subject to higher uncertainty but the investors undervalue the products due to information asymmetry. Therefore, the coefficient of $Higher\ Volatility$ on these products should be negative or insignificant if our incomplete information exploitation story holds. In contrast, a positive coefficient would indicate that underlying uncertainty is driving our main conjecture. In Column (7), we repeat our main regression for the secondary sample that only contains products with a positive $Vega$. In total, this secondary sample consists of 104 products from two product categories, namely Outperformance Certificates and Capital Protection Certificates.[21] The coefficient of $Higher\ Volatility$ is negative and statistically significant, which confirms our information exploitation hypothesis.[22] Even though the coefficient of $Higher\ Dividend$ is of similar magnitude as in the main sample, the coefficient is not statistically significant. One reason is that almost 90% of all products in the secondary sample exhibit $Higher\ Dividend = 1$, and therefore $Higher\ Dividend$ lacks variation to explain $Markup$ with enough statistical power.

We now present several refinements to support our hypothesis that issuers exploit asymmetric information. To this end, we test the interaction terms between our proxies for investors' overvaluation due to information asymmetry and variables that covary with information asymmetry. As a baseline, we use the regression in Column (2) of Table 4. The results are in Table 5.

First, we test the interaction term between $Higher\ Dividend$ and $High\ IBES\ Coverage$. $High\ IBES\ Coverage$ is a binary variable that equals one if the number of analysts that cover a product's underlying ($IBES\ Coverage$) is above the sample median and zero otherwise. We use the number of analysts to proxy for forecast accuracy (Hong and Kacperczyk, 2010). The significantly positive coefficient on the interaction term in Column (1) is consistent with the information exploitation hypothesis because it implies that issuers exploit their privileged access to information more when their information source is more accurate.

Next, we test the interaction between information exploitation and product complexity. We measure product complexity using the methodology of Célérier and Vallée (2017). $High\ Complexity$ is a dummy variable that equals one if a product's complexity ($Complexity$) is above the sample median and zero otherwise. As shown in Column (2), the coefficient of the interaction term between $Higher\ Dividend$ and $High\ Complexity$ is positive and statistically significant. These results speak to the findings of Célérier and Vallée (2017) and Ghent et al. (2017) that higher product complexity is associated with lower ex-post investor performance. Specifically, our results suggest that one explanation for the poor performance of complex securities is that issuers exploit asymmetric information by increasing $Markups$ more if products are more complex. In addition, they imply that product complexity helps issuers to obfuscate the exploitation of asymmetric information.

Next, we analyze if issuers exploit the investors' overvaluation more during times of higher market uncertainty. To this end, we test the interaction terms between our proxies for investors' overvaluation and the variable $High\ VSMI$. $High\ VSMI$ is a binary variable that equals one if the $VSMI$ (the Swiss equivalent to the VIX) at a product's initial fixing date is above the sample median and zero otherwise. The results are presented in Column (3). Both interaction terms are positive and statistically significant. This finding suggests that issuers exploit information asymmetry more when market uncertainty is higher.

In Column (4), we test the interaction between $Higher\ Volatility$ ($Higher\ Dividend$) and $High\ Vega$ ($High\ Delta$). $High\ Vega$ ($High\ Delta$) is a dummy variable that equals one if a product's $Vega$ ($Delta$) is above the sample median.[23] We expect the impact of $Higher\ Volatility$ on $Markups$ to be stronger if $Vega$ is more negative (for low $Vega$ products). Specifically, as the low $Vega$ products' replication prices are more sensitive to volatility information than those of high $Vega$ products, investors overvalue low $Vega$ products more if they underestimate the volatility by a given amount. Therefore, we expect that issuers exploit asymmetric volatility information to a greater extent in the low $Vega$ sample. Similarly, if $Delta$ is high, product replication prices are more sensitive to dividend information. Thus, underestimating a dividend by a given amount leads to a stronger product overvaluation. Therefore, we expect that issuers exploit asymmetric dividend information to a greater extent for products with $High\ Delta = 1$. As shown in Column (4), both interaction terms are not statistically significant.

[19] This comparison assumes that products with a $Higher\ Volatility$ dummy or a $Higher\ Dividend$ dummy equal to zero neither carry an information advantage nor an information disadvantage.

[20] We drop product category fixed effects from this regression because there exists significant overlap between issuer and product categories, for example, one issuer almost exclusively focuses on Barrier Reverse Convertibles.

[21] Table A.1 of the Appendix presents the summary statistics for the secondary sample. Fig. A.1 of the Appendix shows the payoff profiles for the product categories of the secondary sample.

[22] Ideally, we would like to repeat an analysis by analyzing a sample of products for which the products' replication value decreases with the price of the underlying (negative $Delta$). Unfortunately, we are unable to conduct this analysis because our database only contains 14 products that exhibit a negative $Delta$ and simultaneously meet the sample selection criteria.

[23] $Vega$ ($Delta$) is a product value's first-order derivative with respect to the volatility (price) 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 $Vega$ and $Delta$ numerically. We scale each $Delta$ and $Vega$ by the product's initial value to obtain each product's % value-sensitivity.

Table 5
OLS regressions of markups on information measures: Cross-sectional results.

Variables	(1) Markup (in %)	(2) Markup (in %)	(3) Markup (in %)	(4) Markup (in %)	(5) Markup (in %)
Higher Volatility	1.069***	1.019***	0.838***	0.890***	1.291***
	(6.06)	(5.36)	(5.12)	(3.89)	(4.17)
Higher Dividend	0.197	0.088	0.144	0.295*	0.461*
	(1.02)	(0.57)	(0.80)	(1.75)	(1.65)
High IBES Coverage	−0.423**				
	(−2.13)				
Higher Dividend × High IBES Coverage	0.592**				
	(2.20)				
Higher Volatility × High Complexity		0.144			
		(0.39)			
Higher Dividend × High Complexity		0.865***			
		(3.02)			
High VSMI			−0.871***		
			(−3.02)		
Higher Volatility × High VSMI			0.607**		
			(1.98)		
Higher Dividend × High VSMI			0.632**		
			(2.34)		
High Vega				−0.038	
				(−0.17)	
High Delta				−0.227	
				(−1.08)	
Higher Volatility × High Vega				0.376	
				(1.38)	
Higher Dividend × High Delta				0.241	
				(0.90)	
Swiss Stock					1.083***
					(3.00)
Higher Volatility × Swiss Stock					−0.362
					(−0.93)
Higher Dividend × Swiss Stock					−0.244
					(−0.81)
Standard Controls	Yes	Yes	Yes	Yes	Yes
Observations	1012	1012	1012	1012	1012
R-squared	0.295	0.299	0.301	0.294	0.306

This table presents various cross-sectional results for the main specification of our OLS regression approach in Column (2) of Table 4. 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. $High\ IBES\ Coverage$ is a binary variable that is equal to one if a product's $IBES\ Coverage$ is above the sample median and zero otherwise. $High\ Complexity$ is a binary variable that is equal to one if a product's $Complexity$ is above the sample median and zero otherwise. $High\ VSMI$ is a binary variable that is equal to one if the Swiss Volatility Index (VSMI) is above the sample median at a product's initial fixing date and zero otherwise. $High\ Vega$ ($High\ Delta$) is a binary variable that is equal to one if a product's $Vega$ ($Delta$) is above the sample median and zero otherwise. $Swiss\ Stock$ is a dummy that is equal to one if a product's underlying is a Swiss stock and zero otherwise. The standard controls are defined in Table 2. Additionally, we control for year fixed effects and product category fixed effects. The standard errors are clustered at the underlying level. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Motivated by Coval and Moskowitz (2001) who suggest that investors are better informed about local firms, we also test whether issuers exploit asymmetric information less if a product's underlying is a local firm. To this end, we test the interaction between our proxies for investors' overvaluation and a dummy variable that equals one if a product's underlyings is a Swiss stock and zero otherwise. The results presented in Column (5) show that the coefficients of the interaction terms are not statistically significant.

Overall, Section 3 suggests that information asymmetry between issuers and investors is a key factor affecting issuers' product pricing decisions. The literature describes alternative motives for issuers to launch structured products and install large $Markups$ (e.g., Henderson and Pearson, 2011; Célérier and Vallée, 2017; Li et al., 2018). Thus, we neither assert that asymmetric information entirely explains issuers' pricing decision nor controvert that issuers launch products due to alternative motives. We simply highlight that asymmetric information is an important factor that explains a substantial portion of the level and cross-sectional variation of product $Markups$.

4. Issuance volume and asymmetric information

We now investigate the influence of asymmetric information on products' issuance volume. Our premise is that if asymmetric information induces investors to overvalue certain products, banks may push such products to exploit investors' misvaluation.

4.1. Empirical approach

Ideally, we would compare the issuance volume of products with asymmetric information to that of otherwise identical products with symmetric information. Although this ideal setting is not available, we can use an information shock to isolate the impact of asymmetric information on issuance volume. Specifically, we exploit dividend announcements as information shocks. These announcements publicly inform investors about the upcoming dividend payment of a certain product underlying and, hence, reduce the issuers' information advantage due to their privileged access to dividend estimation databases.

The idea of our empirical approach is that products for which the underlying's dividend has recently been publicly announced exhibit lower dividend information asymmetry than products for which the dividend announcement is long ago. Thus, if issuers exploit the dividend information asymmetry by issuing a higher volume of products that investors overvalue due to the dividend information asymmetry, a dividend announcement shortly before product initiation should reduce the issuance volume of such products. As investors tend to overvalue $Higher\ Dividend = 1$ products due to dividend information asymmetry (see Section 3.4), a recent dividend announcement should reveal the overvaluation of these products to investors and, hence, reduce the products' issuance volume. In contrast, dividend information shocks should not impact $Higher\ Dividend = 0$ products' issuance volume because investors do not overvalue the products based on their historical dividend information.

Dividend announcements are a perfect candidate for an exogenous shock to the issuers' information advantage over investors for three reasons. First, issuers cannot influence the date of a dividend announcement. Second, it is unlikely that issuers can avoid product launches around the dividend announcement dates. Specifically, it takes several weeks to plan, structure, market, and issue a new product. As dividend announcement dates vary considerably, issuers would have to stop initiating new products on most underlyings several weeks or months before the public dividend announcement period between March and April to avoid product launches around dividend announcements.[24] The opportunity cost of such a product issuance gap in terms of foregone $Markup$s would probably outweigh the loss of having to issue some products after dividend announcements and, hence, without a dividend information exploitation opportunity. Third, it is unlikely that investors experience a shock to their financial sophistication level at dividend announcement dates, which helps us to isolate information frictions from financial sophistication as a reason behind investor mistakes.

Our treatment variable is based on the time distance of a product underlying's most recent dividend announcement date and the product's initial fixing date. A treated product has the closest dividend announcement date fewer than 100 days but more than seven days before its initial fixing date.[25] We set the time lag to seven days because a product's subscription period can end several days before the initial fixing date, and retail investors tend to react slowly to new information (Hirshleifer et al., 2009). We label treated products using $Dividend\ Announced$, a dummy variable that equals one if the product is treated and zero otherwise. We collect data on dividend announcement dates from Datastream.

Formally, we test the impact of information disclosure on product issuance with the following regression model:

$$IssuanceVolume_i = \alpha + \beta_1 HigherDividend_i x Dividend Announced_i + \beta_j Controls_{ij} + \epsilon_i, \tag{3}$$

where $IssuanceVolume_i$ is the outcome variable and $Dividend\ Announced_i$ is a dummy equal to one if the closest dividend announcement date is fewer than 100 but more than seven days before the initial fixing date, and zero otherwise. β_1 is the coefficient of interest because we focus on the interaction term between $Dividend\ Announced$ and $Higher\ Dividend$. Specifically, if investors invest less in overvalued products when the dividend information shock mitigates the information asymmetry, β_1 should be negative. We control for year fixed effects and product category fixed effects and cluster the standard errors at the underlying level.

[24] The standard deviation of the year-to-year differences between a company's subsequent dividend announcement dates in our sample is more than 30 days.

[25] The dividends of most of the underlyings in our sample are paid out yearly. Thus, the earlier or later dividend announcements are more than one year away from the initial fixing date for most of the underlyings.

4.2. Results

Column (1) of Table 6 presents the results of Regression (3) for our main specification. We find a negative and statistically significant coefficient for the interaction term $Higher\ Dividend\ x\ Dividend\ Announced$. This result confirms that dividend announcements reduce the issuance volume for products that investors tend to overvalue due to information asymmetry. The size of the interaction term's coefficient suggests that the issuance volume of products that investors tend to overvalue due to dividend information asymmetry drops by 29.11% ($e^{-0.344} - 1$) once the public dividend announcement reduces the information asymmetry.

In Columns (2) and (3), we repeat the issuance volume regressions by using 75 and 125 days to construct our $Dividend\ Announced$-dummy. The economic magnitude and statistical significance of the coefficient increase when we use a smaller time window and decrease when we use a larger time window. Next, we address the concern that some firms announce earnings and dividends on the same date, and thus, our results could be driven by earnings announcements. 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 (4) to (11) in the Appendix contain a dividend component but not an earnings component. Consequently, earnings are not a plausible price-relevant information friction for structured products. Therefore, earnings announcements should not affect issuance volume. Besides this intuitive theoretical argument, we provide statistical evidence that earnings information shocks do not drive our conjecture. To this end, we repeat our main product issuance analysis but exclude all products for which the earnings announcement date occurs within one month of the dividend announcement and before the initial fixing date. Column (4) shows that our results are robust to this exclusion.

Overall, we find evidence that closing the information gap between issuers and investors reduces the issuance volume of products that investors tend to overvalue. Excess security issuance is prominently debated in the financial innovation literature because it raises concerns about increasing systemic risk (Gennaioli et al., 2012; Hanson and Sunderam, 2013). Our results suggest that reducing information asymmetry can mitigate this concern.

5. Product design and asymmetric information

Issuers have considerable flexibility to tailor structured products (Henderson and Pearson, 2011; Célérier and Vallée, 2017), which allows us to analyze the impact of asymmetric information on product design. Specifically, we investigate whether issuers systematically select underlyings with a higher implied than historical volatility and a higher forecasted than historical dividend, that is, underlyings for which investors have a stronger tendency to overvalue structured products.

We start by defining the set of underlyings issuers may select for structured products. We assume this available set consists of all underlyings in the main sample that have been chosen by any issuer during our observation period. For each week and underlying in the available set, we calculate $Implied\ Volatility$, $Historical\ Volatility$, $Forecasted\ Dividend$, and $Historical\ Dividend$ for a time to maturity of 255 days. We choose this time span because it corresponds to the median product maturity in our sample. We proxy investors' tendency to overvalue a structured product due to information asymmetry regarding volatility and dividend with the $Higher\ Volatility$ and $Higher\ Dividend$ dummies defined in Section 3.2, respectively.

We first use this data to estimate a panel model, in which we regress the number of issued products on a certain underlying in a week ($Number\ of\ Products$) on our information friction proxies and a

Table 6
OLS regressions of products' issuance volume.

Variables	(1) Issuance volume	(2) Issuance volume	(3) Issuance volume	(4) Issuance volume
Window	[−7, −100]	[−7, −75]	[−7, −125]	[−7, −100]
Higher Dividend × Dividend Announced	−0.344*	−0.426*	−0.311	−0.330*
	(−1.79)	(−1.91)	(−1.64)	(−1.67)
Dividend Announced	−0.004	0.059	−0.031	0.003
	(−1.55)	(0.31)	(−0.19)	(0.02)
Higher Dividend	−0.015	−0.013	−0.020	0.011
	(−0.25)	(−0.23)	(−0.35)	(0.18)
Markup (in %)	0.001	0.003	0.002	−0.000
	(0.09)	(0.22)	(0.13)	(−0.03)
Higher Volatility	0.150**	0.156**	0.155**	0.134*
	(2.20)	(2.39)	(2.27)	(1.79)
Forecasted Dividend	0.751	0.522	0.938	0.057
	(0.37)	(0.26)	(0.46)	(0.03)
Implied Volatility	−0.435	−0.528	−0.389	−0.298
	(−1.01)	(−1.23)	(−0.88)	(−0.62)
Market Cap	0.171***	0.171***	0.174***	0.175***
	(5.20)	(5.11)	(5.35)	(4.64)
3 m Excess Return	−0.289	−0.249	−0.257	−0.265
	(−1.43)	(−1.20)	(−1.26)	(−1.09)
12 m Excess Return	−0.011	−0.033	−0.021	−0.138
	(−0.07)	(−0.22)	(−0.14)	(−0.81)
1 m Turnover	0.208**	0.202*	0.207*	0.182
	(1.97)	(1.88)	(1.96)	(1.56)
3 m Turnover	−0.253**	−0.249**	−0.254**	−0.227*
	(−2.32)	(−2.27)	(−2.33)	(−1.89)
1 m Call Option Volume	2.342	2.019	2.283	1.702
	(1.27)	(1.19)	(1.22)	(0.97)
1 m Put Option Volume	−2.794	−2.537	−2.808	−2.283
	(−1.43)	(−1.39)	(−1.42)	(−1.22)
Constant	16.275***	16.304***	16.264***	16.283***
	(68.78)	(68.63)	(68.44)	(57.34)
Without Earnings	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes
Product Category FE	Yes	Yes	Yes	Yes
Observations	826	826	826	741
R-Squared	0.456	0.456	0.456	0.453

This table presents the results for our issuance volume regressions. The dependent variable is the issuance volume ($IssuanceVolume$), which is the natural logarithm of a structured product's issuance volume (in USD). In Columns (1) and (4), we define $Dividend\ Announced$ as a binary variable that is equal to one if the dividend announcement date closest to the initial fixing date occurs fewer than 100 days but more than 7 days before the product's initial fixing date and zero otherwise. In Column (2) (Column (3)), we define $Dividend\ Announced$ as a binary variable that is equal to one if the dividend announcement date closest to the initial fixing date occurs fewer than 75 (125) days but more than 7 days before the product's initial fixing date and zero otherwise. In Column (4), we exclude products for which the dividend announcement date closest to the initial fixing date occurs before the product's initial fixing date and within 30 days of an earnings announcement. The standard controls are defined in Table 2. Additionally, we control for year fixed effects and product category fixed effects. The standard errors are clustered at the underlying level. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

set of controls. We also include year fixed effects and underlying fixed effects. We lag the independent variables by up to four weeks because issuers need to determine the basic product characteristics, such as the underlying before the initial fixing date, that is, at the time they initiate a product launch process (see Section 2 and Egan (2019)). If issuers launch more products on a certain underlying when investors tend to overvalue products with this underlying, the variables $Higher\ Volatility$ and $Higher\ Dividend$ should have a positive coefficient.

Table 7 summarizes the results of the panel regressions. Columns (1) to (3) suggest that the number of products issued on a certain underlying increases when investors tend to overvalue products with this underlying ($Higher\ Volatility$ or $Higher\ Dividend$ equal to one). Depending on the number of lags, issuers launch, on average, up to 0.009 (0.016) products more per week on underlyings with $Higher\ Volatility$ ($Higher\ Dividend$) equal to one. As the average number of issued products on an underlying per week is 0.045 in our sample, the estimated coefficients correspond to an increase of 20% ((0.045 + 0.009) / 0.045) for the underlyings with $Higher\ Volatility$ equal to one and 36% ((0.045 + 0.016) / 0.045) for the underlyings with $Higher\ Dividend$ equal to one. Whereas the coefficients are statistically significant for all lags with $Higher\ Dividend$, it is only significant for a lag of three weeks with $Higher\ Volatility$.

Next, we provide graphical evidence of the issuers' selection timing for the products' underlying. Panel A in Fig. 3 plots the average difference of the portion of $Higher\ Volatility = 1$ underlyings between selected underlyings and those from the available set that are not selected around the initial fixing date. It shows that around three to four weeks before the initial fixing date, which usually corresponds to the product launch and the beginning of the subscription period, the selected underlyings are more likely to have $Higher\ Volatility = 1$ compared to the underlyings in the available set. Panel B shows that this pattern regarding the timing of the underlying selection is even more pronounced for $Higher\ Dividend = 1$ underlyings. Specifically, the average difference is significant over the entire product launch and subscription period until the initial fixing date. Overall, the graphs suggest that issuers time the selection of the products' underlyings such that investors tend to overvalue structured products due to information asymmetry during the period in which the investors buy the products.

Table 7
OLS regressions of underlying choice.

Variables	(1) Number of products	(2) Number of products	(3) Number of products
Lag	4 Weeks	3 Weeks	2 Weeks
Higher Volatility	0.009	0.009*	0.003
	(1.61)	(1.79)	(0.59)
Implied Volatility	0.000	0.000	−0.000
	(0.92)	(0.29)	(−0.32)
Higher Dividend	0.016**	0.015**	0.015**
	(2.13)	(2.01)	(2.09)
Forecasted Dividend	−0.001	−0.001	−0.002*
	(−0.96)	(−0.98)	(−1.69)
Market Cap	0.017	0.020	0.023
	(1.27)	(1.39)	(1.63)
3 m Excess Return	0.011	0.027	0.039*
	(0.45)	(1.25)	(1.83)
12 m Excess Return	−0.019	−0.024*	−0.033**
	(−1.39)	(−1.69)	(−2.18)
1 m Turnover	−0.010*	−0.017**	−0.006
	(−1.72)	(−2.17)	(−0.87)
3 m Turnover	0.023***	0.030***	0.019*
	(2.82)	(2.90)	(1.94)
1 m Put Option Volume	0.308	0.508**	0.536*
	(1.37)	(2.50)	(1.93)
1 m Call Option Volume	−0.155**	−0.160**	−0.185**
	(−2.46)	(−2.37)	(−2.54)
Constant	−0.350**	−0.373**	−0.382**
	(−2.42)	(−2.40)	(−2.50)
Year FE	Yes	Yes	Yes
Underlying FE	Yes	Yes	Yes
Observations	18,895	18,966	19,033
R-squared	0.047	0.051	0.052

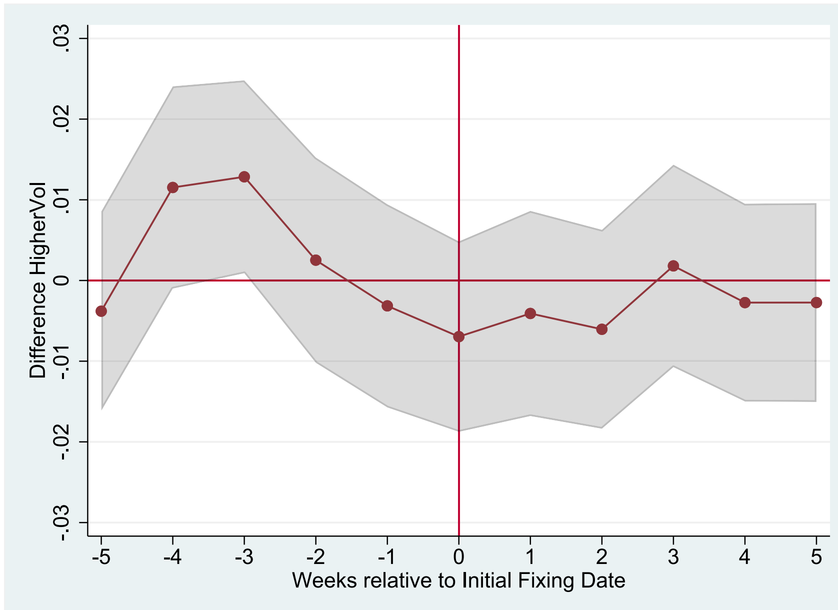
This table presents the results of the issuers' underlying selection using OLS panel regressions. The dependent variable is the number of products ($Number\ of\ Products$) issued on a certain underlying in the same week. $Implied\ Volatility$ is the annualized implied volatility of the product's option on the underlying calculated over the next 255 trading days. We calculate $Historical\ Volatility$ as the standard deviation of a product underlying's returns over the 255 trading days before the observation date. $Higher\ Volatility$ is a binary variable that is equal to one if $Implied\ Volatility$ is larger than $Historical\ Volatility$ and zero otherwise. $Forecasted\ Dividend$ is the ratio between the present value of forecasted dividend payments based on IBES that occur over the next 255 trading days and the stock price of the underlying at the observation date. We define $Historical\ Dividend$ as the ratio between the present value of the dividend payments that occur during the next 255 trading days estimated from the historical dividend payment pattern and the stock price of the underlying at the observation date. $Higher\ Dividend$ is a binary variable that is equal to one if $Forecasted\ Dividend$ is larger than $Historical\ Dividend$ and zero otherwise. The control variables are defined in Table 2. We control for year fixed effects and underlying fixed effects. Depending on the specification of the model, the independent variables are lagged by two, three, and four weeks. The standard errors are clustered at the underlying level. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Our panel regression and the simple graphical representation neglect potential unobservable variation over time and across underlyings that may affect issuers' tendency to select a certain underlying (Roberts and Whited, 2013). Thus, we also employ a matched-sample approach to compare investors' tendency to overvalue structured products due to information asymmetry of the underlyings that issuers select for a product with otherwise similar underlyings that they do not select. Specifically, for each underlying that issuers actually choose for a structured product, we 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.[26] As matching variables, we apply the underlying specific control variables from Section 3. In addition, 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 products to the category "Other".

Next, we calculate the portions of the chosen underlyings and the matched underlyings for which the $Higher\ Volatility$ 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 8 shows that whereas 61.4% of the chosen underlyings have an implied volatility that is larger than the historical volatility, only 56.8% of the matched underlyings carry this feature. Using the one-sided t-test, we find that this difference is statistically significant. Economically, chosen underlyings are, on average, 8.1% ((61.4–56.8)/56.8) more likely to have a $Higher\ Volatility$ dummy equal to one than matched underlyings. We also calculate the portions of the chosen underlyings and the matched underlyings for which the $Higher\ Dividend$ dummy is equal to one. We find that 69.9% of the chosen underlyings and 63.3% of the matched underlyings carry a $Higher\ Dividend$ dummy equal to one. Again, this difference is highly statistically and economically significant. Specifically, chosen underlyings are, on average, 10.4% ((69.9–63.3)/63.3) more likely to carry a $Higher\ Dividend$ dummy equal to one than matched underlyings. Columns (2) and (3) show that the results are similar if we lag the matching variables by three or two weeks.

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

Panel A: Difference in Higher Volatility between selected and not selected Underlyings around Product Initial Fixing Date



Panel B: Difference in Higher Dividend between selected and not selected Underlyings around Product Initial Fixing Date

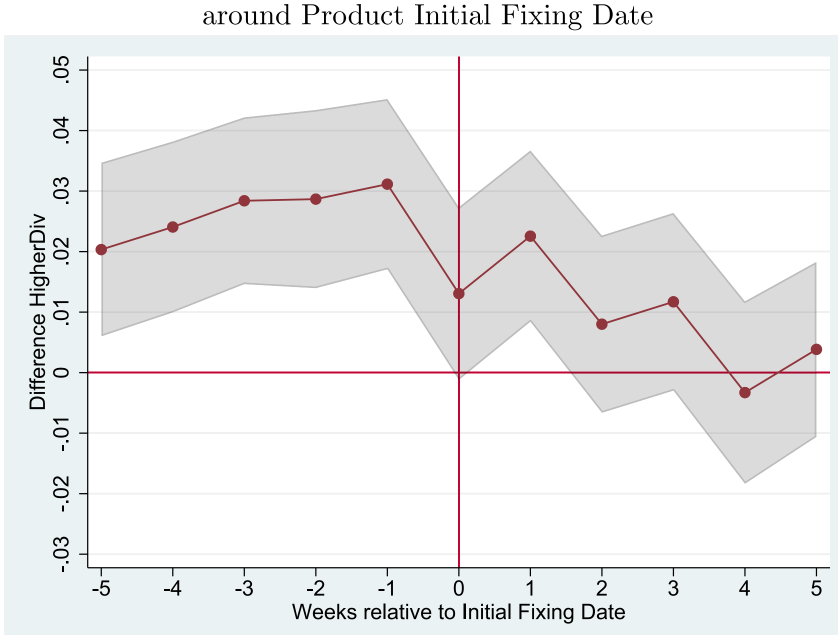


Fig. 3. Underlying selection around product issuance date.
These figures plot issuers' underlying selection decision over time around initial fixing dates. In Panel A, we plot the average difference between the portion of underlyings with $Higher\ Volatility = 1$ that are selected as underlyings and the portion of underlyings with $Higher\ Volatility = 1$ of the underlyings from the available set that are not selected. In Panel B, we plot the average difference between the portion of underlyings with $Higher\ Dividend = 1$ that are selected as underlyings and the portion of underlyings with $Higher\ Dividend = 1$ of the underlyings from the available set that are not selected. We assume that the available set consists of all underlyings in the main sample that have been chosen by any issuer during our observation period. The gray areas represent the 90% confidence intervals.

In Panel B of Table 8, we also calculate the average value of $Implied\ Volatility$ and $Forecasted\ Dividend$ for both chosen underlyings and matched underlyings. An alternative driver of our results could be that because retail investors lack the sophistication to recognize the negative impact of volatility and dividends on structured products' replication prices, issuers would tend to select underlyings with higher

Table 8
Nearest neighbor matching for underlying choice.

Panel A:	(1)	(2)	(3)
Lag	4 Weeks	3 Weeks	2 Weeks
Mean Higher Volatility Issued	0.614	0.615	0.598
Mean Higher Volatility Matched	0.568	0.569	0.560
Mean Difference Higher Volatility	0.046**	0.046**	0.038*
	(0.03)	(0.03)	(0.05)
Mean Higher Dividend Issued	0.699	0.703	0.701
Mean Higher Dividend Matched	0.633	0.644	0.637
Mean Difference Higher Dividend	0.067***	0.059***	0.064***
	(0.00)	(0.00)	(0.00)
Panel B:	(1)	(2)	(3)
Lag	4 Weeks	3 Weeks	2 Weeks
Mean Implied Volatility Issued	29.549	29.338	29.247
Mean Implied Volatility Matched	28.896	28.833	28.810
Mean Difference Implied Volatility	0.653	0.505	0.438
	(0.14)	(0.20)	(0.22)
Mean Forecasted Dividend Issued	3.053	2.999	2.956
Mean Forecasted Dividend Matched	2.841	2.847	2.774
Mean Difference Forecasted Dividend	0.212*	0.152	0.287
	(0.08)	(0.15)	(0.10)

This table presents the results of the issuers' underlying selection using a Nearest Neighbor Matching approach. For each underlying that issuers actually choose for a structured product in the main sample, 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. $Higher\ Volatility$ ($Higher\ Dividend$) is a binary variable that is equal to one if $Implied\ Volatility$ ($Forecasted\ Dividend$) is larger than $Historical\ Volatility$ ($Historical\ Dividend$) and zero otherwise. $Mean\ Difference\ Higher\ Volatility$ ($Mean\ Difference\ Implied\ Volatility$) is calculated as the difference between the value of $Higher\ Volatility$ ($Implied\ Volatility$) of the underlying that is actually chosen and the mean value of $Higher\ Volatility$ ($Implied\ Volatility$) of the matched underlyings. $Mean\ Difference\ Higher\ Dividend$ ($Mean\ Difference\ Forecasted\ Dividend$) is calculated as the difference between the value of $Higher\ Dividend$ ($Forecasted\ Dividend$) of the underlying that is actually chosen and the mean value of $Higher\ Dividend$ ($Forecasted\ Dividend$) of the matched underlyings. Depending on the specification of the model, the matching variables are lagged by two, three, and four 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.

$Implied\ Volatility$ and $Forecasted\ Dividend$ to boost $Markup$s. Except for $Mean\ Difference\ Forecasted\ Dividend$ in Column (1), however, none of the differences is significantly above zero. Thus, our result in Panel A of Table 8, that issuers select underlyings for which investors have a stronger tendency to overvalue structured products cannot be explained by investors' missing financial sophistication.[27]

Overall, our product design analysis implies that exploiting information asymmetry is an important reason for issuers to select certain product underlyings and launch new structured products. This result is crucial for the financial stability debate because it underpins the concern that financial engineering creates investor information frictions in the market for innovative securities, which can cause large market disruptions (Gennaioli and Shleifer, 2010; Hanson and Sunderam, 2013).

6. Robustness tests

We now conduct robustness tests for our main results. In Table 9, we report alternative specifications of the main regressions presented in Table 4. We include $Implied\ Volatility$, $Higher\ Volatility$, $Forecasted\ Dividend$, and $Higher\ Dividend$ in all regression specifications.

To incorporate a potential non-linear relationship between volatility or dividend and $Markup$, we additionally consider the square product of $Implied\ Volatility$ ($Implied\ Volatility\ Squared$) and $Forecasted\ Dividend$ ($Forecasted\ Dividend\ Squared$) in our regression model. Column (1) of Tables 9 show that the results for $Higher\ Volatility$ and $Higher\ Dividend$ are robust to this specification.

A systematic error in the calculation of $Implied\ Volatility$ could introduce a correlation between our independent variable $Markup$ and the control variables $Implied\ Volatility$ or $Higher\ Volatility$ 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 $Implied\ Volatility$. 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 $Implied\ Volatility$ 182 and $Higher\ Volatility$ 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 9 shows that the $Higher\ Volatility$ 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 $Higher\ Volatility$ with $Higher\ Volatility$ 126 in Column (3) of Table 9. The only difference in this specification is that we calculate the historical volatility used in $Higher\ Volatility$ 126 over half a year (126 trading days) instead of 255 trading days prior to the initial fixing date. Thus, $Higher\ Volatility$ 126 is a binary variable that is equal to one if $Implied\ Volatility$ is larger than the historical standard deviation of a product underlying's returns over the previous 126 trading days and

[27] As an alternative test, we repeat the matching procedure by including $Implied\ Volatility$ and $Forecasted\ Dividend$ as matching variables. The chosen underlyings are still significantly more likely to have $Higher\ Volatility$ and $Higher\ Dividend$ dummies equal to one than the matched underlyings (not tabulated).

Table 9
Robustness tests: OLS regressions of markups on information measures.

Variables	(1) Markup (in %)	(2) Markup (in %)	(3) Markup (in %)	(4) Markup (in %)
Higher Volatility	0.976***			0.426**
	(5.53)			(2.22)
Higher Volatility 182		0.579***		
		(2.89)		
Higher Volatility 126			0.862***	
			(4.97)	
Implied Volatility	0.179***		0.054***	0.149***
	(3.82)		(5.11)	(7.63)
Implied Volatility Squared	−0.002***			
	(−2.90)			
Implied Volatility 182		0.002		
		(0.19)		
Higher Dividend	0.488***	0.337**	0.475***	0.398**
	(3.07)	(2.02)	(2.91)	(2.22)
Forecasted Dividend	0.106	−0.020	0.021	0.057
	(1.01)	(−0.42)	(0.44)	(1.08)
Forecasted Dividend Squared	−0.008			
	(−0.59)			
Historical Volatility				−0.078***
				(−6.13)
Historical Dividend				−0.010
				(−1.04)
HH-Index				0.242
				(0.08)
CDS Spread				0.085
				(0.43)
Economic Environment				0.033**
				(2.23)
Funding Needs				3.197
				(1.62)
Time to Maturity				0.668*
				(1.90)
Short-term Product				0.509**
				(2.12)
VSMI				−0.040**
				(−2.22)
Constant	−6.126***	−1.834	−4.016**	−8.089***
	(−3.62)	(−1.26)	(−2.61)	(−3.63)
Standard Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Product Category FE	Yes	Yes	Yes	Yes
Observations	1012	994	1012	1011
R-squared	0.305	0.219	0.277	0.351

This table presents various robustness tests for our $Markup$ regression results in the main sample. 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. $Implied\ Volatility$ is the annualized implied volatility of the product's option on the underlying calculated for the lifetime of the product. We calculate $Historical\ Volatility$ as the standard deviation of a product underlying's returns over the 255 trading days before the initial fixing date. $Higher\ Volatility$ is a binary variable that is equal to one if $Implied\ Volatility$ is larger than $Historical\ Volatility$ and zero otherwise. $Implied\ Volatility\ Squared$ is calculated as the square product of $Implied\ Volatility$. $Forecasted\ Dividend$ 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 $Historical\ Dividend$ as the ratio between the present value of the dividend payments that occur during the next 255 trading days estimated from the historical dividend payment pattern and the stock price of the underlying at the observation date. $Higher\ Dividend$ is a binary variable that is equal to one if $Forecasted\ Dividend$ is larger than $Historical\ Dividend$ and zero otherwise. $Forecasted\ Dividend\ Squared$ is the square product of $Forecasted\ Dividend$. $Implied\ Volatility$ 182 is the annualized implied volatility of an at-the-money put option on the product's underlying with a maturity of 182 days. $Higher\ Volatility$ 182 is a binary variable that is equal to one if $Implied\ Volatility$ 182 is larger than $Historical\ Volatility$ and zero otherwise. $Higher\ Volatility$ 126 is a binary variable that is equal to one if $Implied\ Volatility$ is larger than the standard deviation of a product underlying's returns over the 126 trading days before the initial fixing date and zero otherwise. $HH-Index$ 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. $VSMI$ 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 and category fixed effects. The standard errors are clustered at the underlying level. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

zero otherwise. The coefficient of $Higher\ Volatility$ 126 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 specifications.

Next, we include a battery of additional control variables that could affect our results in Column (4) of Table 9. We incorporate $Historical\ Volatility$ and $Historical\ Dividend$ to account for the concern that historical information could drive the results for our proxies $Higher\ Volatility$ and $Higher\ Dividend$, 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.[28]

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.

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 $Markups$.

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 ($Short-term\ Product$).[29]

Another potential concern with our volatility result is that a volatility risk premium in the spirit of, for example, 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 proxies for investors' tendency to overvalue structured products due to asymmetric information $Higher\ Volatility$ and $Higher\ Dividend$ play a significant role in explaining $Markup$s is robust to these additional controls (see Column (4) of Table 9). In addition, the coefficient of $Historical\ Volatility$ is significantly negative, indicating that issuers reduce $Markup$ when an underlying recently exhibits a high volatility.[30] We also find a significantly positive relation between the economic environment and $Markup$s. As expected, products with a longer $Time\ to\ Maturity$ have larger $Markup$s. In addition, products with a tax advantage ($Short-term\ Product$) exhibit a significantly larger $Markup$. $VSMI$ is significantly negative, suggesting higher market uncertainty reduces $Markup$s. The remaining control variables are insignificant.

7. Conclusion

The exploitation of household mistakes by financial institutions is a crucial concern, not only from an investor protection perspective but also because this exploitation can lead to financial fragility and corrosive mistrust in the financial system (Gennaioli et al., 2012; Zingales, 2015; Campbell, 2016). There is an ongoing debate on the channels behind this exploitation in the market for innovative securities, including product complexity, investor sophistication, and behavioral biases (e.g., Carlin, 2009; Zingales, 2015; Célérier and Vallée, 2017; Li et al., 2018). In this study, 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. This information gap has important explanatory power for the existence and cross-sectional variation of $Markups$. Thus, our study highlights asymmetric information as another key channel behind household mistake exploitation.

Identifying the reasons for household mistakes is important because alternative reasons call for alternative regulatory measures. For example, insufficient investor sophistication calls for educational effort, which can be cost-inefficient or suffer from low participation rates (Cole et al., 2011; Bruhn et al., 2014), whereas asymmetric information calls for disclosure. Disclosure appears to have largely escaped regulators in charge of investor protection and market stability. For instance, the Dodd-Frank Act only broadly suggests that issuers should disclose adequate information to investors. Disclosure policies, however, suffer from at least three drawbacks. First, publicly disclosing more information can benefit or harm welfare (Bond and Goldstein, 2015; Goldstein and Yang, 2019). Second, even if information is disclosed, disclosure processing costs can impose additional frictions that affect investors' choices (Blankespoor et al., 2020). Third, the effect of disclosure on mitigating investor mistakes tends to be modest (e.g., Choi et al., 2009). Our study highlights, however, that besides reducing household mistakes, disclosure may also be important to discipline product issuers' behavior. Specifically, we find that disclosure reduces issuers' issuance volume for products that investors tend to overvalue due to information asymmetry. In addition, our product design results show that issuers select underlyings for which investors have a stronger tendency to overvalue structured products. These behavioral aspects are a concern from a financial stability perspective because they suggest that issuers create information frictions in the financial innovation market, which can lead to large market disruptions (Gennaioli et al., 2012; Hanson and Sunderam, 2013). Thus, we believe that such behavioral aspects are additional dimensions that should be incorporated in further research discussing the implications of information disclosure for household finance.

Data availability

Data will be made available on request.

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.

Products of the Main Sample

We replicate Discount Certificates (DC) as

$$DC = \frac{M}{exp(rT)} - P(S - PV(D), M, T, \sigma_P), \tag{4}$$

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

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

[30] If we include $Historical\ Volatility$ as a control variable, the model exhibits considerable multicollinearity measured by the Variance Inflation Factor. The coefficient of $Higher\ Volatility$ remains significantly positive if we exclude $Historical\ Volatility$ from the model in Column (4).

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. This adjustment is necessary because, in contrast to a direct investment in an underlying stock, a structured product investor is not entitled to receive the stock's dividend payments. This convention applies to all product categories. σ_P is the implied volatility of the put option with corresponding strike and maturity.

We replicate a Barrier Discount Certificate (BDC) as

$$BDC = \frac{M}{exp(rT)} + C(S-PV(D), Y, T, \sigma_C) - DIP(S-PV(D), X, B, T, \sigma_{DIP}), \quad (5)$$

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

$$RC = \frac{N}{exp(rT)} + \sum_{t_i \le T} \frac{c_{t_i}}{exp(rt_i)} - \alpha P(S - PV(D), X, T, \sigma_P), \quad (6)$$

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

$$\begin{aligned} COC = {} & \frac{M}{exp(rT)} - P(S - PV(D), M, T, \sigma_P) + \\ & (\alpha - 1)C(S - PV(D), Y, T, \sigma_{C1}) - (\alpha - 1)C(S - PV(D), M, T, \sigma_{C2}), \end{aligned} \quad (7)$$

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

$$BRC = \frac{N}{exp(rT)} + \sum_{t_i \le T} \frac{c_{t_i}}{exp(rt_i)} - \alpha DIP(S - PV(D), X, B, T, \sigma_{DIP}), \quad (8)$$

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}.

We construct Bonus Certificates (BC) using

$$\begin{aligned} BC = {} & \frac{M}{exp(rT)} + C(S - PV(D), M, T, \sigma_C) - \\ & P(S - PV(D), M, T, \sigma_P) + \alpha DOP(S - PV(D), M, B, T, \sigma_{DOP}), \end{aligned} \quad (9)$$

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}.

Products of the Secondary Sample

As a robustness test, we also analyze product categories that exhibit a positive vega. We construct these product categories as follows: We replicate Outperformance Certificates (OC) as

$$OC = \frac{M}{exp(rT)} - P(S - PV(D), M, T, \sigma_P) + \alpha C(S - PV(D), M, T, \sigma_C), \quad (10)$$

where M is the redemption amount of the bond component, α is the total participation rate, and $C(S-PV(D), M, T, \sigma_C)$ is a call option with strike M, time to maturity T, and implied volatility σ_C.

Finally, we replicate Capital Protection Certificates (CPC) as

$$CPC = \frac{N}{exp(rT)} + \sum_{t_i \le T} \frac{c_{t_i}}{exp(rt_i)} + \alpha C(S - PV(D), X, T, \sigma_C), \quad (11)$$

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 $C(S - PV(D), X, T, \sigma_C)$ is a put option on the underlying of the product with strike X, time to maturity T, and implied volatility σ_C. α reflects the number of call options contained in the nominal amount of one certificate.

We obtain the option components for a replication price by transforming traded (American) EUREX option prices into the (European) option prices of the 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.

Table A.1
Descriptive statistics for the secondary sample.

Dependent variables	Mean	Std. Dev.	Q10	Median	Q90
Markup (in %)	3.37	3.09	0.14	2.77	6.56
Explanatory Variables	Mean	Std. Dev.	Q10	Median	Q90
Implied Volatility (in %)	21.16	5.26	16.05	19.81	28.75
Historical Volatility (in %)	20.24	6.26	15.30	18.43	26.62
Higher Volatility	0.79	0.41	0	1	1
Higher Dividend	0.88	0.32	0	1	1
Market Cap	4.37	0.77	3.57	4.58	5.03
3 m Excess Return (in %)	−2.15	7.91	−12.56	−1.25	7.57
12 m Excess Return (in %)	−6.84	14.10	−21.97	−7.60	9.83
1 m Turnover	7.73	1.89	3.94	8.54	9.06
3 m Turnover	8.86	1.87	5.15	9.72	10.15
1 m Call Option Volume (in %)	2.68	4.49	0.16	1.44	5.48
1 m Put Option Volume (in %)	1.81	2.69	0.10	1.18	4.30
Issuance Volume	16.02	1.04	14.19	16.29	17.08

This table presents descriptive statistics for the secondary sample that contains the structured products issued in Switzerland between January 2005 and December 2010 on a single equity underlying with a positive $Vega$. The sample consists of 104 products. Markup ($Markup$) is the issue price of a structured product minus its replication price, scaled by the issue price, expressed in percentage points. $Implied\ Volatility$ is the annualized implied volatility of the product's option on the underlying calculated for the lifetime of the product. We calculate $Historical\ Volatility$ as the standard deviation of a product underlying's returns over the 255 trading days before the initial fixing date. $Higher\ Volatility$ is a binary variable that is equal to one if $Implied\ Volatility$ is larger than $Historical\ Volatility$ and zero otherwise. $Market\ Cap$ is the natural logarithm of the market value of equity of the underlying (in USDbn). 3 m and 12 m $Excess\ Return$ 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. 1 m and 3 m $Turnover$ 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 1 m $Call\ Volume$ and 1 m $Put\ Volume$ 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).

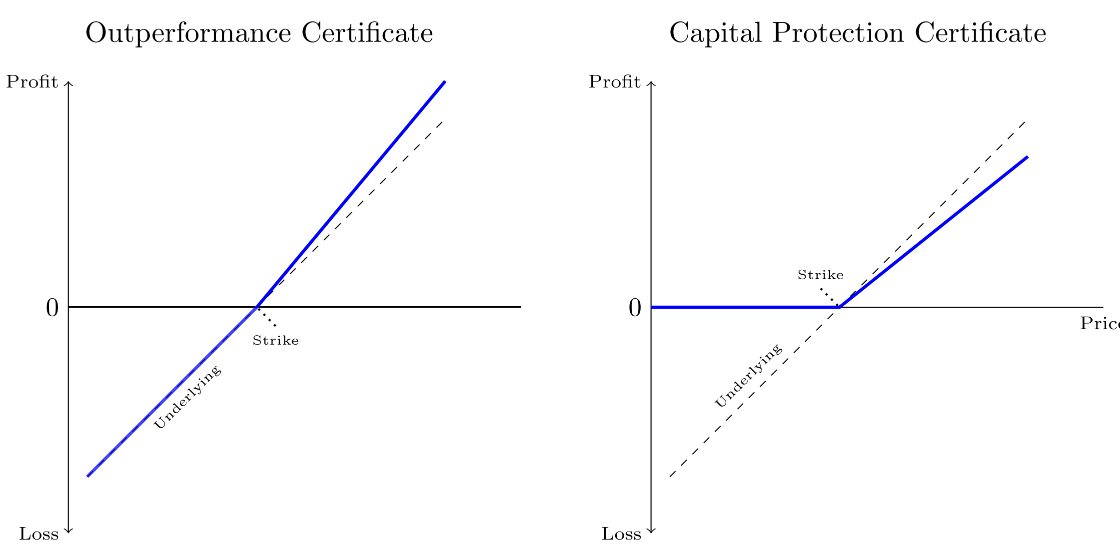


Fig. A.1. Payoff profiles for the secondary sample.
This figure illustrates the payoff profiles of the product categories in our secondary sample. Each graph depicts the payoff in the nominal currency of the product with respect to the product's underlying reference price at its final fixing date.

Table A.2
OLS Regressions of the markups on information measures: Index products.

Variables	(1) Markup (in %)	(2) Markup (in %)
Higher Volatility	1.525**	1.449***
	(2.20)	(6.50)
Implied Volatility	0.050*	0.035
	(1.91)	(0.82)
Div Yield	0.008**	0.013***
	(2.32)	(4.80)
3 m Excess Return	−0.019***	−0.013
	(−3.85)	(−1.00)
12 m Excess Return	−0.035***	−0.000
	(−4.73)	(−0.03)
1 m Call Option Volume	−0.275***	−0.263***
	(−6.87)	(−25.08)
1 m Put Option Volume	0.246***	0.245***
	(4.65)	(14.78)
Constant	−3.360***	−5.662***
	(−10.31)	(−3.35)
Year FE	Yes	Yes
Product Category FE	Yes	No
Underlying FE	No	Yes
Issuer FE	No	Yes
Observations	119	119
R-squared	0.451	0.582

This table presents the results of OLS regressions for the sample with Index products. 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. $Implied\ Volatility$ is the annualized implied volatility of the product's option on the underlying calculated for the lifetime of the product. We calculate $Historical\ Volatility$ as the standard deviation of a product underlying's returns over the 255 trading days before the initial fixing date. $Higher\ Volatility$ is a binary variable that is equal to one if $Implied\ Volatility$ is larger than $Historical\ Volatility$ and zero otherwise. $Div\ Yield$ is the annualized dividend yield of the product's underlying. The standard controls are defined in Table 2. We control for year fixed effects and product category fixed effects. Depending on the specification of the regression, we additionally control for issuer and underlying fixed effects. The standard errors are clustered at the underlying level. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

References

Affinito, M., Tagliaferri, E., 2010. Why do (or did?) banks securitize their loans? Evidence from Italy. J. Financial Stab. 6, 189–202.

Allen, F., Gale, D., 1988. Optimal security design. Rev. Financ. Stud. 1 (3), 229–263.

An, X., Deng, Y., Stuart, G., 2011. Asymmetric information, adverse selection, and the pricing of CMBS. J. Financ. Econ. 100, 304–325.

Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. J. Finance 61 (1), 259–299.

Arnold, M., Schuette, D., Wagner, A., 2021. Neglected risk in financial innovation: Evidence from structured product counterparty exposure. Eur. Financial Manag. 27 (2), 287–325.

Ashcraft, A.B., Schuermann, T., 2008. Understanding the securitization of subprime mortgage credit. Federal Reserve Bank of New York Staff Report, Vol. 318.

Baule, R., Entrop, O., Wilkens, M., 2008. Credit risk and bank margins in structured financial products: Evidence from the German secondary market for Discount Certificates. J. Futures Mark. 28 (4), 376–397.

Ben-Rephael, A., Da, Z., Israelsen, R.D., 2017. It depends on where you search: Institutional investor attention and underreaction to news. Rev. Financ. Stud. 30 (9), 3009–3047.

Bhattacharya, U., Hackethal, A., Kaesler, S., Loos, B., Meyer, S., 2012. Is unbiased financial advice to retail investors sufficient? Answers from a large field study. Rev. Financ. Stud. 25, 975–1032.

Blankespoor, E., deHaan, E., Marinovic, I., 2020. Disclosure processing costs, investors' information choice, and equity market outcomes: A review. J. Account. Econ. 70 (2–3).

Bloomberg Brief: Structured Notes, 2015. 2014 Year in review. Special Report.

Bond, P., Goldstein, I., 2015. Government intervention and information aggregation by prices. J. Finance 70, 2777–2811.

Bouveret, A., Crisóstomo, R., Gentile, M., Mendes, V., Pereira da Silva, P., Silva, F., 2013. Economic report: Retailisation in the EU. European Securities and Markets Authority.

Bruhn, M., Ibarra, G.L., McKenzie, D., 2014. The minimal impact of a large-scale financial education program in Mexico City. J. Dev. Econ. 108, 184–189.

Burth, S., Kraus, T., Wohlwend, H., 2001. The pricing of structured products in the Swiss market. J. Deriva. 9 (2), 30–40.

Calvet, L.E., Célérier, C., Sodini, P., Vallée, B., 2022. Can security design foster household risk-taking? J. Finance forthcoming.

Campbell, J., 2006. Household finance. J. Finance 61, 1553–1604.

Campbell, J., 2016. Restoring rational choice: The challenge of consumer financial regulation. Amer. Econ. Rev. 106 (5), 1–30.

Carlin, B.I., 2009. Strategic price complexity in retail financial markets. J. Financ. Econ. 91, 278–287.

Carlin, B., Manso, G., 2011. Obfuscation, learning, and the evolution of investor sophistication. Rev. Financ. Stud. 24 (3), 754–785.

Carr, P., Wu, L., 2016. Analyzing volatility risk and risk premium in option contracts: A new theory. J. Financ. Econ. 120, 1–20.

Célérier, C., Vallée, B., 2017. Catering to investors through security design: Headline rate and complexity. Q. J. Econ. 132, 1469–1508.

Chang, E.C., Tang, D.Y., Zhang, M.B., 2015. Suitability checks and household investments in structured products. J. Financ. Quant. Anal. 50, 597–622.

Choi, J., Laibson, D., Madrian, B., 2009. Why does the law of one price fail? An experiment on index mutual funds. Rev. Financ. Stud. 23, 1405–1432.

Cole, S., Sampson, T., Zia, B., 2011. Prices or knowledge? What drives demand for financial services in emerging markets? J. Finance 66 (6), 1933–1967.

Coval, J., Jurek, J., Stafford, E., 2009. The economics of structured finance. J. Econ. Perspect. 23, 3–25.

Coval, J.D., Moskowitz, T.J., 2001. The geography of investment: Informed trading and asset prices. J. Polit. Econ. 109 (4), 811–841.

Cox, J., Ross, S., Rubinstein, M., 1979. Option pricing: A simplified approach. J. Financ. Econ. 7, 229–263.

Daniel, K., Hirshleifer, D., Teoh, S.H., 2002. Investor psychology in capital markets: Evidence and policy implications. J. Monetary Econ. 49, 139–209.

DeMarzo, P., 2005. The pooling and tranching of securities: A model of informed intermediation. Rev. Financ. Stud. 18, 1–35.

Duffie, D., Rahi, R., 1995. Financial market innovation and security design: An introduction. J. Econom. Theory 65 (1), 1–42.

Egan, M., 2019. Brokers vs. Retail investors: Conflicting interests and dominated products. J. Finance 74, 1217–1260.

ESMA, 2022. Performance and costs of EU retail investment products. ESMA Annual Statistical Report.

European Structured Investment Products Association, 2021. EUSIPA market report, Q4 2021. Quarterly report.

Gabaix, X., Laibson, D., 2006. Shrouded attributes, consumer myopia, and information suppression in competitive markets. Q. J. Econ. 121, 505–540.

Gennaioli, N., Shleifer, A., 2010. What comes to mind. Q. J. Econ. 125, 1399–1433.

Gennaioli, N., Shleifer, A., Vishny, R., 2012. Neglected risks, financial innovation, and financial fragility. J. Financ. Econ. 104, 452–468.

Ghent, A.C., Torous, W.N., Valkanov, R.I., 2017. Complexity in structured finance. Rev. Econom. Stud. 86 (2), 694–722.

Goldstein, I., Yang, L., 2019. Good disclosure, bad disclosure. J. Financ. Econ. 131 (1), 118–138.

Gorton, G., Metrick, A., 2012. Securitized banking and the run on Repo. J. Financ. Econ. 104, 425–451.

Greenwood, R., Scharfstein, D., 2013. The growth of finance. J. Econ. Perspect. 27 (2), 3–28.

Hanson, S.G., Sunderam, A., 2013. Are there too many safe securities? Securitization and the incentives for information production. J. Financ. Econ. 108, 565–584.

Henderson, B.J., Pearson, N.D., 2011. The dark side of financial innovation: A case study of the pricing of a retail financial product. J. Financ. Econ. 100, 227–247.

Henderson, B.J., Pearson, N.D., Wang, L., 2020. Pre-trade hedging: Evidence from the issuance of retail structured products. J. Financ. Econ. 137 (1), 108–128.

Hirshleifer, D., Lim, S.S., Teoh, S.H., 2009. Driven to distraction: Extraneous events and underreaction to earnings news. J. Finance 64 (5), 2289–2325.

Hong, H., Kacperczyk, M., 2010. Competition and bias. Q. J. Econ. 125 (4), 1683–1725.

Hull, J.C., 2009. Options, Futures, and Other Derivatives. Pearson, Prentice Hall.

Kurlat, P., Stroebel, J., 2015. Testing for information asymmetries in real estate markets. Rev. Financ. Stud. 28, 2429–2461.

Li, X., Subrahmanyam, A., Yang, X., 2018. Can financial innovation succeed by catering to behavioral preferences? Evidence from a callable options market. J. Financ. Econ. 128, 38–65.

Piskorski, T., Seru, A., Witkin, J., 2015. Asset quality misrepresentation by financial intermediaries: Evidence from the RMBS market. J. Finance 70, 2635–2678.

Roberts, M.R., Whited, T.M., 2013. Endogeneity in empirical corporate finance. In: Handbook of the Economics of Finance, Vol. 2. pp. 493–572.

Ross, S.A., 1989. Institutional markets, financial marketing, and financial innovation. J. Finance 44 (3), 541–556.

Shiller, R., 2003. The New Financial Order: Risk in the 21st Century. Princeton University Press.

Sirri, E.R., Tufano, P., 1998. Costly search and mutual fund flows. J. Finance 53, 1589–1622.

SSPA, Swiss Structured Products Association, 2013. Market report structured products. Quarterly report.

Stein, J.C., 2012. Monetary policy as financial-stability regulation. Q. J. Econ. 127, 57–95.

Stoimenov, P.A., Wilkens, S., 2005. Are structured products fairly priced? An analysis of the German market for equity-linked instruments. J. Bank. Financ. 29 (12), 2971–2993.

Stroebel, J., 2016. Asymmetric information about collateral values. J. Finance 71 (3), 1071–1112.

Structured Retail Products, 2015. Analysis on structured products and listed equity options in Europe: An industry overview and future prospects. Research Report for the Options Industry Council.

Swiss Bankers Association, 2007. Guidelines on informing investors about structured products.

Vokata, P., 2021. Engineering lemons. J. Financ. Econ. 142 (2), 737–755.

Wallmeier, M., Diethelm, M., 2009. Market pricing of exotic structured products: The case of multi-asset barrier reverse convertibles in Switzerland. J. Deriva. 17 (2), 59–72.

Zingales, L., 2015. Presidential address: Does finance benefit society? J. Finance 70 (4), 1327–1363.