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

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

November 9, 2017

Abstract

This paper investigates the impact of imperfect investor information on financial innovation. We identify volatility and dividends as specific information sources for which issuers of financially engineered products have an information advantage over retail investors. Issuers' information advantage is crucial to explaining the overpricing and design of financially engineered products. We confirm our conjecture that issuers exploit this information channel by analyzing a discontinuity in issuers' information advantage. The insights are of systemic importance because they suggest that product issuers' behavior in the financial innovation market aggravates investor information frictions in the financial system.

JEL-Code: D8, G34, M52

Keywords: Structured products, investor information, financial innovation

* We thank Allaudeen Hameed, Anastasia Kartasheva, Angelo Ranaldo, Jens Jackwerth, Joel Peress, John Gathergood, Luigi Guiso, Marcel Fischer, Markku Kaustia, Markus Schmid, Martin Brown, Matthias Pelster, Nic Schaub, Nicolas Kube, Pierre Collin-Dufresne, Samuli Knüpfer, Yakov Amihud, participants of the Topics in Finance Workshop in Davos, the Helsinki Finance Summit on Investor Behavior, the brown bag seminar in St.Gallen, the German Finance Association Conference, and the Swiss Society for Financial Market Research Conference for helpful comments. We also thank Derivative Partners for providing the structured products database and the "s/bf-HSG Sponsors Association" for funding.

[†] University of St.Gallen, School of Finance, Switzerland, e-mail: manuel.ammann@unisg.ch

[‡] University of St.Gallen, School of Finance, Switzerland, e-mail: marc.arnold@unisg.ch

[§] University of St.Gallen, School of Finance, Switzerland, e-mail: simon.straumann@unisg.ch

1 Introduction

A dark side of financial innovation is that retail investors' investment mistakes have large welfare costs (Schiller, 2003). One source of such mistakes, namely imperfect investor information, has attracted particular attention since the 2007–2008 credit crisis because of concerns that this friction causes dramatic market disruptions (Gennaioli, Shleifer, and Vishny, 2012; Hanson and Sunderam, 2013). Information disclosure is, therefore, at the forefront of the current regulatory efforts to improve financial market stability and increase welfare. As Campbell (2006) stresses in his presidential address, disclosure requirements can reduce the incidence of investment mistakes, but the challenge is to design these requirements appropriately. A key prerequisite to tackle the challenge is a deep understanding of the role and origin of imperfect investor information in financial innovations. Yet, the exact origin of the information friction is largely unknown mainly because investors' information sets are usually not observable.

This paper investigates imperfect investor information in the market for structured products. We overcome the information-observability challenge through our access to a large database containing the information provided to structured product investors. Our analysis provides two primary results. First, we identify two specific information sources that cause issuers to exploit their informational advantage over retail investors, namely volatility and dividends. Both information types are economically important determinants of product overpricing, whereas standard proxies for the production cost of structured products, market environment, and liquidity are mostly insignificant. Second, issuers design products towards the sources of investor information frictions that we identify. The design result is of systemic importance because it underpins the concern that financial engineering aggravates imperfect investor information frictions in financial markets.

Structured products have recently attracted attention in the financial innovation literature because of issuers' flexibility to tailor these products to the desired function

(Henderson and Pearson, 2011; Célérier and Vallée, 2017). They represent an ideal laboratory in which we can explore the role of imperfect information on financial innovations, as they are frequently issued to retail investors with information that is inferior to the information held by financial intermediaries (Bhattacharya et al., 2012). In addition, issuers' flexibility allows us to analyze the impact of their informational advantage on product design.

We have access to a large database containing the term sheets of all structured products on single stock underlyings issued in Switzerland. The market for structured products is well established in Europe and has, according to the SEC database, also grown substantially in the US in recent years Bouveret et al. (2013). Issuers of structured products are obliged to disclose important product information to investors on term sheets. Comparing term sheet information that is available to investors with the (costly) financial information available to product issuers from EUREX and IBES allows us to measure the informational gap between issuers and investors. Using the term sheets, we also calculate the difference between product issue prices to retail investors and replication prices for identical payout profiles to institutional investors. We label this difference the issue premium (IP). The IP measures the premium at which issuers sell products to retail investors and, hence, the % overpricing of these products. Analyzing price differences helps us to isolate the impact of the informational gap because any unobservable price determinant that is correlated with our informational proxies should affect both prices but not their difference.

We first examine product issuers' exploitation of their volatility information advantage. Whereas issuers have access to implied volatility estimates of a product's underlying, term sheets do not disclose this information. Instead, retail investors tend to rely on historical price discovery (Daniel et al., 2002; Sirri and Tufano, 1998), which is commonly provided on term sheets. We find that issuers earn a 64% (95 bps) larger IP with products for which the implied volatility is higher than the historical volatility. As replication prices in our sample decline with implied volatility, this relationship suggests that issuers earn higher IPs when investors, based on their information set, overvalue a product. We present a battery of refinements to confirm that issuers exploit their volatility information advantage. First, the effect is stronger for products that are more value-sensitive to volatility information, have less coverage from implied volatility providers, and have a higher portion of retail investors. Second, products with higher implied than historical volatility tend to have relatively low implied volatility. Thus, the result is not simply a consequence of investors' being unable to recognize that higher implied volatility reduces product prices (Henderson and Pearson, 2011). Third, using a matched sample approach, we show that issuers select underlying stocks with a higher implied than historical volatility when designing their products.

We then analyze issuers' dividend information exploitation. Product values in our sample decline with expected dividends because investors are long in the underlying stock, but do not obtain dividends that accrue up to maturity. Whereas issuers have access to dividend estimates, term sheets do not disclose this information. The dividend results mirror our observations from the volatility analysis. Issuers earn a 53% (78 bps) higher IP with products for which analysts forecast a higher future underlying dividend than the publicly available historical dividend. We also find that issuers' tendency to exploit this information channel is stronger when product value-sensitivity to dividends is higher and the portion of retail investors is larger. In addition, a matched sample approach reveals that issuers select underlying stocks with a higher forecasted than historical dividend.

Although we take care to consider price differentials, relevant controls, robustness tests, and refinements to exclude alternative explanations of our results, the challenge in claiming causality between imperfect investor information and security issuance behavior is the difficulty of isolating differences in issuers' informational advantage independently of observable and unobservable product, macroeconomic, competition, or issuer characteristics. We address this identification problem by exploring a discontinuity in issuers' informational advantage regarding the timing of underlying dividends. Specifically, a structured product's payoff is specified with respect to the stock price at maturity and investors are not entitled to receive the underlying's dividend. Thus, investors overvalue a product if they expect the share price at maturity to still trade cum-dividend but it already trades ex-dividend. This overvaluation due to incomplete dividend payment date information can only occur with products that have an ex-dividend date shortly before maturity (just–before products), but not for those that have the ex-dividend date right after maturity (just–after products).[1] Therefore, issuers are able to exploit superior dividend timing information only with just–before products. We explore this discontinuity in issuers' informational advantage around future ex-dividend dates using a standard Regression Discontinuity Design (RDD). We find that whereas just–before products have observable characteristics that are very similar to those of just–after products, the former are discontinuously more overpriced than just–after products. This result confirms that issuers use their informational advantage to push overpriced securities to investors.

Our results relate to several streams of the literature. First, a vein of closely related studies analyzes the reasons behind investors' mistakes in the financial innovation market. This literature finds that product complexity, ignorance of fees, obfuscation, or lack of sophistication can partially explain the mistakes (DeMarzo, 2005; Coval et al., 2009; Choi et al., 2009; Carlin, 2009; Carlin and Manso, 2011; Henderson and Pearson, 2011; Célérier and Vallée, 2017). We contribute to this literature by identifying investors' inferior access to financial information as an important additional explanation.

Second, we contribute to the literature that points to imperfect investor information as a crucial friction in the financial innovation market (Ashcraft and Schuermann, 2008; An et al., 2011). Gennaioli et al. (2012), Gorton and Metrick (2012), Stein (2012), and Hanson and Sunderam (2013) argue that this friction is tenuous to the entire financial system as it can cause large market disruptions when new information arrives. Despite

[1]In case just–after product investors expect the ex-dividend date to be earlier than the true date, their misjudgment could even induce them to undervalue a structured product.

this concern, surprisingly little is known about the sources behind imperfect investor information. An exception is the study of Piskorski et al. (2015), which finds significant asset quality misrepresentation by issuers of residential Mortgage-Backed Securities. We contribute to this literature in two ways. First, we identify volatility and dividends as two important sources behind the investor information friction. As the recent disclosure literature suggests that the type of information being disclosed is key in determining whether disclosure is welfare improving (Bond and Goldstein, 2015; Goldstein and Yang, 2017), knowing the specific sources is crucial for guiding policymakers in the design of appropriate disclosure measures that mitigate the friction. Second, our results pertaining to the design of structured products emphasize the systemic stability concern, implying that financial innovators deliberately structure products for which investors have inferior information.

Third, we complement studies on the pricing of structured products. According to this stream of the literature, it is challenging to explain variations in structured products' IPs. Henderson and Pearson (2011) analyze the mispricing of 64 retail structured products. Out of nine potential explanatory variables, only one (implied volatility of the underlying) is significantly associated with IPs. Benet et al. (2006) also find a substantial IP. They show that both an underlying's implied volatility and product maturity play a role. Stoimenov and Wilkens (2005) investigate the secondary market prices of structured products. We contribute to this literature stream by illustrating that imperfect investor information is an economically important pricing determinant.

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. They are composed of multiple financial instruments, commonly a combination of bonds, equities and derivatives. Structured products are issued to investors on the primary market and subsequently traded on the secondary market until they expire. In this study, we focus on the primary market, for two reasons. First, the secondary market is relatively illiquid and has a much lower traded volume than the issue volume on the primary market (SVSP, Schweizerischer Verband für Strukturierte Produkte, 2013). Second, we are also interested in issuers' design of products, which is determined at issue, and not only in issuers' price setting decision.

Issuers have considerable flexibility to tailor the products by choosing the composition, underlying, option strikes, and issue pricing.[2] This flexibility in product design raises the concern that issuers exploit investors by using their privileged access to information. It also weakens the competition mechanism as a potential remedy to this concern because issuers can impede comparability of their products to those of competitors by simply issuing different product designs. Regulations limit issuers' flexibility along certain dimension.[3] For example, pure forward and option transactions do not qualify as structured products. In addition, products with a maturity beyond one year are subject to the stamp tax in Switzerland.[4] The latter regulation limits issuers' flexibility to select product maturities, which is important for our regression discontinuity approach.

The market for structured products has grown substantially. Bouveret et al. (2013) report a total outstanding volume of structured products in Europe of almost EUR 770bn as of December 2012. This notional volume amounts to 4% of household financial wealth, or 12% of mutual funds' assets under management in the European market. Whereas the US structured product 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 USD

[2] Whereas issue prices are normalized for some products, issuers can simply determine the amount of each instrument that such a normalized product package contains and, hence, the issue pricing.

[3] see the regulatory framework "Guidelines on informing investors about structured products" published by the Swiss Bankers Association and approved by the Swiss Federal Banking Commission.

[4] The taxation of structured products is regulated in the circular letter issued by the Federal Tax Adminstration on April 12, 1999 (not available in English).

0.3bn in the year 2000 to USD 43.5bn in the year 2015. Most products have equity underlyings both from the US and Europe (Bloomberg Brief: Structured Notes, 2015; Structured Retail Products, 2015).

In this study, we focus on a large database of structured products issued in the Swiss market. Banks in this market rely on standardized product categories, which is important for the systematic collection of comparable products (Structured Retail Products, 2015). With a total sales volume of USD 21.3bn, Switzerland was the second largest European issuer of structured products in 2014 (Structured Retail Products, 2015). The Swiss market has also been the global leader in terms of the volume of structured products invested in custody accounts (Swiss Bankers Association, 2011).

Our structured products database is provided by Derivative Partners. It contains term sheets of all structured products on equity underlyings issued in Switzerland between January 2005 and December 2010. The database comprises 15'170 publicly issued products that target the retail market.[5]

From this database, we exclude products on multiple underlyings (14'138) and with missing data (20), leaving us with a total sample of 1012 products on a single equity underlying. We focus on products with a single equity underlying because they can be replicated from observed market prices of interest rates and EUREX options on the corresponding underlying.[6] The availability of market prices is important for investigating the difference between structured product prices for retail investors and replication (market) prices for institutional investors. Our sample of priced products is considerably larger than those used in existing studies. For example, Henderson and Pearson (2011) consider 64 products, Célérier and Vallée (2017) price 141 products, and Arnold et al. (2016) extract 501 products from the same structured products database.

Table 1 reports the number of launched products grouped by issuer, product category,

[5]Above a minimum investment threshold of around CHF 25'000, most issuers in the Swiss market offer individual structuring of products on behalf of clients. These tailor-made products are issued privately and, hence, are not included in the database.

[6]EUREX options data are provided by the FMI department of the Karlsruhe Institute of Technology.

and year. The products were 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 each year, whereas it declined between 2008 and 2010.

INSERT TABLE 1 NEAR HERE

Product payoff profiles are defined in the term sheets. On the initial fixing date, the issuing bank defines the terms of a structured product such as the issue price, strikes, coupon payments, barrier level, redemption, and all relevant dates. These terms are communicated to an investor in a product's final term sheet. Derivative Partners provides a database which lists all final term sheet items for every structured product, we manually double-check each database entry with the corresponding term sheet.[7] Product categories in our sample have the following profiles:

With a *Discount Certificate*, an investor purchases an underlying stock at a discount but resigns the upside stock performance beyond a prespecified cap. If the stock closes above this cap at maturity, the investor obtains a payoff equal to the difference between the initial stock and the strike prices. Otherwise, he 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 the product's lifetime. If this barrier is touched, the capital protection is cancelled 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.

[7] In total, we find and correct 31 entries that contain an error mostly in the date item.

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 as long as the underlying stock does not touch a prespecified lower barrier during a product's lifetime. If the barrier is touched, the capital protection is canceled and a Barrier Reverse Convertible 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. Once the barrier is touched, the down-side protection is canceled and the Bonus Certificate simply follows the stock performance.

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

3 Product overpricing and imperfect information

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

3.1 Overpricing measure: Issue premium

We use the IP of structured products as our dependent variable. The IP is the percentage difference between the issue price and the replication price of a structured product

(Henderson and Pearson, 2011). We calculate IP as

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

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 are directly associated with the products. Due to their access to fixed income and option markets, institutional investors can replicate the payoff profile of a structured product with traded instruments. Thus, the *Replication Price* is the market price for institutional investors of replicating a product's payoff profile. Intuitively, the IP is the percentage difference between prices for retail and institutional investors of the same payout profile at the same time. As a product issuer can hedge his future obligation to a retail investor when selling a structured product by simply replicating the payoff profile, the IP reflects the percentage product overpricing at issue and, hence, the issuer's profit for launching a product.[8]

Whereas product term sheets provide us with issue prices, we also need to calculate 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 presented in Table 2, the average issue premium in our sample is 1.48%. This magnitude coincides with the average IP 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, IPs tend to be higher. The studies of Stoimenov and Wilkens (2005) on the German market and of Henderson and Pearson (2011) on the US market find average issue premiums of 3.89% and more than 8%, respectively.

[8]We control for additional factors affecting hedging costs in our analysis.

INSERT TABLE 2 NEAR HERE

3.2 Imperfect information: Volatility and dividends

We investigate the information provided by issuers to structured product investors to define our explanatory variables that capture imperfect information. This information is collected in product term sheets. The term sheets disclose most parameters that are relevant to assessing the value of a structured product. Thus, it is relatively easy even for less financially sophisticated retail investors to compare term sheet information between products. For instance, a product with a higher coupon is more attractive than a product with a lower coupon but otherwise identical term sheet information. It is, however, more challenging for retail investors to compare products along dimensions that are not exposed on term sheets. Therefore, we argue that it is simpler for issuers to sell structured products to retail investors that are overpriced in terms of product characteristics which are not observable on term sheets. Two important replication price determinants of structured products, on which there is no information on term sheets, are the implied volatility of the underlying and the expected dividend.

We define implied volatility ($Impl\ Vola$) as 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 from traded EUREX options as described in the Appendix.

$Impl\ Vola$ is available to product issuers through, for example, EUREX or BLOOMBERG. It is, however, difficult for retail investors to obtain implied volatility estimates because access to traded options data is restricted and costly; e.g., one year of access to BLOOMBERG's proprietary computer system costs around $25,000 per user. Hence, retail investors must resort to alternative measures when gauging the expected volatility of a product's underlying. As suggested by the literature (Daniel et al., 2002; Sirri and Tufano, 1998), they tend to rely on historical information. This conjecture is supported by our observation that many structured product term sheets contain a picture of the historical price evolution of the product's underlying.[9]. To capture the volatility information available to retail investors, we, therefore, calculate the historical volatility (*Hist Vola*) as the standard deviation of a product underlying's returns over the 255 trading days before the initial fixing date. We choose 255 days as it corresponds to the median product maturity in our sample. The average implied and historical volatilities are 0.29% and 0.31%, respectively, as shown in Table 2. Whereas they are of similar average magnitude, historical volatility has a larger standard deviation.

Because replication prices of all products in our sample decline with volatility, issuers have an informational advantage over retail investors if *Impl Vola* is larger than *Hist Vola*. In this case, retail investors underestimate volatility based on their available information and, hence, overestimate a product's value. Thus, we proxy issuers' volatility information advantage with the simple dummy variable *Higher Vola* that is one if *Impl Vola* is larger than *Hist Vola*. For 563 of the 1012 products in our sample the *Higher Vola* dummy is one. We use a dummy in the primary analysis to avoid that our results are driven by, for example, large negative differences between the two volatility measures that are difficult to interpret. Section 6 shows that the results are robust to using the difference between *Impl Vola* and *Hist Vola* as a proxy of the informational advantage. Our first hypothesis is that issuers overprice products more when they have a volatility information advantage.

The expected dividends of a product's underlying are a second crucial pricing factor, which is not provided in product term sheets. Product issuers usually have access to dividend forecasts such as IBES. We capture the issuers' dividend information (*IBES Div*) as the ratio between the present value of expected dividend payments based on IBES forecasts that occur during a product's lifetime and the underlying's stock price at the initial fixing date. We estimate the expected ex-dividend dates by projecting the historical ex-dividend dates within a year prior to the initial fixing date into the future.

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

Dividend forecasts are restricted and costly. Retail investors can instead resort to historical dividend information, which is publicly available on the Internet, to estimate expected dividends.[10] We capture retail investors' dividend information by *Hist Dividend*, which is the ratio between the present value of expected dividend payments based on historical dividend amounts paid in the 255 days prior to the initial fixing date and the underlying's stock price at the initial fixing date. *IBES Dividend* and *Hist Dividend* have similar means and quantiles as shown in Table 2. Both dividend measures are characterized by a relatively low standard deviation.

Structured product investors are usually not entitled to receive dividend payments because they hold only derivative positions on the underlying. Since the replication prices of all products in our sample are positively related to the stock price of the underlying (all products exhibit a delta that is strictly above zero), a higher future dividend payment during the lifetime of a structured product ceteris paribus reduces the product's current replication price. Thus, issuers have an informational advantage over retail investors if *IBES Div* is larger than *Hist Div*. In this case, retail investors underestimate dividends based on their available information and, hence, overestimate a product's value. Therefore, we proxy issuers' dividend information advantage with the simple dummy variable *Higher Div* that is one if *IBES Div* is larger than *Hist Div*. For 608 of the 1012 products in our sample, *Higher Div* is equal to one. We use a dummy in the primary analysis to avoid that our results are driven by, for example, large negative differences between the two dividend measures that are difficult to interpret. Section 6 shows that the results are robust to using the difference between *IBES Div* and *Hist Div* as a proxy of the informational advantage. Our second hypothesis is that issuers overprice products more when they have a dividend information advantage.

The correlation between *Higher Vola* and *Higher Div* is 0.08. Thus, the two dummy variables identify mainly two distinct product groups.

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

3.3 Empirical approach and identification

To investigate the impact of imperfect information on product overpricing, we run cross-sectional OLS regressions of IP on our explanatory and control variables. Our main regression model is

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

where IP_i is the IP of product i. $Higher\, Dummy_i$ represents our information advantage proxy, which is the $Higher\ Vola$ dummy for volatility and the $Higher\ Div$ for dividends. Hence, $Higher\, Dummy_i$ is our main explanatory variable.

Our main identification challenge arises from potential omitted variables that are correlated with both IPs and an explanatory variables. We mitigate this challenge by incorporating a comprehensive set of controls and considering price differences as the dependent variable.

First, we incorporate the control variables of Henderson and Pearson (2011) into our analysis, which are captured in the vector of controls $Controls_{ij}$.[11] Specifically, we control for investor attention ($ExcessReturn$, $Market\ Cap$ and $Underlying\ Turnover$) and issuers' hedging costs ($Option\ Volume$). We calculate $Excess\ Return$ as the return of 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 natural logarithm of the dollar value (in USDm) of the cumulated 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 cumulated 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

[11] The only control to which we do not have access is the issuance volume of each product.

by the volume of call (put) options written on all underlyings during the same time period. As in Henderson and Pearson (2011), we also consider year fixed effects in all regressions to control for aggregate trends such as in product demand. In Section 6, we incorporate additional control variables. Our results are robust to including measures for competition, issuers' default risk, funding needs, the economic environment, products' time to maturity, product complexity, product category fixed effects, issuer fixed effects, and underlying fixed effects. All data on underlyings, options components, and dividend consensus estimates are from Datastream, the EUREX database, and IBES, respectively. We present the summary statistics for all controls in Table 2.

Second, the advantage of using IP as the dependent variable is that IP is a price differential, which mitigates the omitted variables concern. Specifically, if unobserved variables (similarly) affect $Issue\ Price$ and *Replication Price*, their impact on our results cancels out in the differential and, hence, they do not bias our estimation.

Finally, we enhance the credibility of our informational explanation by showing that the relation between the dependent and the explanatory variables is stronger when the information channel is more plausible. To this end, we interact our explanatory variables with several additional variables that are included in Table 2. *Delta* ($Vega$) is a product's first-order derivative with respect to the price (volatility) of the underlying using the Black-Scholes formula, scaled by the product's denomination. *Delta* ($Vega$) of products with barrier options is calculated numerically. The $Vega$ of all our products is negative and the *Delta* positive, which implies that investors gain from volatility reductions, underlying price increases, or expected dividend cuts during a product's lifetime. In addition, we collect structured products' trading size because the literature finds a negative relationship between trading size and investor sophistication (Battalio and Mendenhall, 2005; Bhattacharya et al., 2007; Bhattacharya, 2001). Specifically, we calculate $Trading\ Size$ as the logarithm of the average trading size of each structured product in USD on the secondary market and use this variable as a proxy for the sophistication of a product's investors. We also consider *IVolatility*, which is a dummy variable that is one if a product's underlying is covered on IVolatility.com at the initial fixing date and zero otherwise. IVolatility.com is a widely used volatility information provider.[12] It is the first provider that offers single volatility quotes on selected individual underlyings to retail investors, whereas alternative providers only offer entire volatility information packages. This single quote feature is important in the context of our study because IVolatility.com coverage of an underlying considerably reduces the volatility information advantage of issuers over retail investors for that underlying. Specifically, a structured product investor could acquire the volatility information of a product with a covered underlying for a few dollars but would have to buy the entire volatility package for several thousand dollars if he wanted the volatility information of an uncovered underlying.[13] For 768 products in our sample, volatility information on underlyings was available on IVolatility.com at the initial fixing date.

Another identification challenge is to establish a causal link between issuers' informational advantage and product overpricing. We address this challenge by applying a regression discontinuity approach in Section 4.

3.4 Overpricing and imperfect volatility information

We start by investigating the impact of imperfect volatility information on *IPs*. In Column (1) of Table 3, we first replicate the regression of Henderson and Pearson (2011) to ensure that our setting is consistent with their study. As in Henderson and Pearson (2011), only *Impl Vola* is positively associated with *IPs*. The remaining controls are either insignificant or not robust to alternative controls (see Columns (1)–(5)).

INSERT TABLE 3 NEAR HERE

Next, we test our hypothesis by adding the *Higher Vola* dummy in Column (2).

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

[13] The charge for single quotes starts at 3 USD.

The coefficient on $Higher\ Vola$ implies that issuers demand a 0.951% larger IP for products with higher implied than historical volatility. This magnitude is important, accounting for almost two-third of average IPs. This result suggests that issuers overprice products when they have a volatility information advantage, i.e., when retail investors underestimate volatility based on their historical information. A caveat with our $Higher\ Vola$ dummy is that it could be correlated with a volatility risk premium. Whereas this premium affects option prices (e.g., Carr and Wu, 2016), the advantage of using IP in our regressions is that the IP corresponds to the difference between prices paid by retail and institutional investors. Thus, even if the volatility risk premium affects option prices, it should not drive the price difference of the same option.

We address the concern that $Higher\ Vola$ simply identifies products with particularly high $Impl\ Vola$ by calculating the average $Impl\ Vola$ of products that have a $Higher\ Vola$ dummy of one. Their average $Impl\ Vola$ (0.265%) is significantly smaller than that of products with a $Higher\ Vola$ dummy of zero (0.314%), with a t-statistics of 6.93 using a two-sample t-test. Thus, issuers also increase IPs when $Impl\ Vola$ is relatively small yet larger than the historical volatility and not simply when $Impl\ Vola$ is large. Therefore, imperfect information plays a role that is independent of the financial literacy explanation in Henderson and Pearson (2011). This literacy explanation would imply that because retail investors are unaware of the negative impact of volatility on structured products' replication prices, issuers would simply install larger IPs for products with higher $ImplVola$.

To investigate whether the quantitative magnitude of the $Higher\ Vola$ coefficient is consistent with our information exploitation story, we first calculate the difference between the implied and historical volatilities for all products with $Higher\ Vola$ equal to one. The approximate value of a product's informational advantage for an issuer is then retrieved by multiplying this difference by the product $Vega$. Intuitively, this value is a retail investor's percentage overvaluation of a product if he or she relies on the historical instead of the implied volatility. Issuers' average informational advantage value across all products with a dummy equal to one is 1.859%. Thus, the coefficient of $Higher\ Vola$ in Column (2) suggests that issuers are, on average, able to exploit approximately 51% (0.951% of 1.859%) of their informational advantage. The economic magnitude of this exploitation is plausible given that approximately half of all products in Switzerland are sold to retail investors (SVSP, Schweizerischer Verband für Strukturierte Produkte, 2013) and that $Higher\ Vola$ is only a proxy of issuers' volatility informational advantage.

We now present several refinements to support our first hypothesis that issuers exploit imperfect volatility information.

If the exploitation of imperfect volatility information drives our results, then the coefficient on $Higher\ Vola$ should be more pronounced for products with a more negative $Vega$. For such products, investors overestimate product values particularly when they underestimate volatility. Indeed, the coefficient on the interaction $Higher\ Vola$ x $Vega$ in Column (3) shows that if $Vega$ is more negative, the impact of $Higher\ Vola$ on IPs is stronger.

In Column (4), we investigate how the coverage of a product's underlying at the issue date on IVolatility.com affects our results. The negative and significant coefficient of the interaction term between $Higher\ Vola$ and $IVolatility$ implies that, consistent with our hypothesis, improving retail investors' volatility information accessibility mitigates issuers' exploitation of this information advantage channel.[14] A potential explanation for the result that exploitation declines with investor information accessibility is the reputation concern of issuers. This channel may work independent of whether investors actually collect that information.

As shown in Column (5), the interaction between $Higher\ Vola$ and $Trading\ Size$ as a proxy for investor sophistication has a significantly negative coefficient. This result

[14] If we include underlying fixed effects, the coefficient of the interaction term is equal to −0.53 and statistically significant at the 10% level. Thus, the effect is not driven by underlying specific characteristics but the change in the availability of implied volatility information.

also supports our imperfect information exploitation hypothesis because it implies that issuers particularly use their informational advantage to overprice securities when investor sophistication is low.

3.5 Overpricing and imperfect dividend information

We now test whether product issuers exploit their informational advantage regarding dividends. The results are presented in Table 4. In the first column, we include *IBES Div* as a measure of forecasted dividend payments. The significantly positive coefficient of *IBES Div* shows that an increase in expected dividend yield raises the *IP*. The magnitude of the coefficient implies that increasing *IBES Div* by one standard deviation (0.022) enhances the *IP* by 0.15%.

INSERT TABLE 4 NEAR HERE

We incorporate our proxy for retail investors' information on dividends in Column (2). Products with *Higher Div* equal to one carry an *IP* that is on average 0.783% higher. This effect is economically important because it corresponds to an increase of more than 52% of the average *IP*. These results provide a first indication regarding our second hypothesis that issuers collect higher *IPs* if they have a dividend information advantage over retail investors.

To investigate whether the quantitative magnitude of the *Higher Div* coefficient is consistent with our information exploitation story, we first calculate the difference between the present values of expected IBES dividends and historical dividends over the lifetime of all products with *Higher Div* equal to one. We then obtain the approximate value of a product's informational advantage for an issuer by multiplying this difference by the product *Delta*. Intuitively, this value is a retail investor's percentage overvaluation of a product if he or she relies on historical instead of forecasted dividends. Issuers' average informational advantage value across all products with a dummy equal to one is 1.465%. Thus, the coefficient of *Higher Div* included in Column (2) suggests that issuers are, on average, able to exploit around 54% (0.783% of 1.465%) of their informational advantage. The economic magnitude of this exploitation is plausible given that approximately half of all products in Switzerland are sold to retail investors (SVSP, Schweizerischer Verband für Strukturierte Produkte, 2013) and that *Higher Div* is only a proxy for issuers' informational advantage.

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

Column (4) shows that the interaction between *Higher Div* and *Trading Size* has a significantly negative coefficient. This result supports the information exploitation hypothesis because it implies that issuers use their dividend information advantage in particular to overprice securities when investor sophistication is low.

Overall, Section 3 suggests that volatility and dividend are two key information sources that cause the investor information friction. They explain a substantial part of the level and cross-sectional variation of the products' overpricing.

4 A regression discontinuity design for dividend payments around the maturity date

Product issuers have privileged access to dividend timing information that is unavailable to retail investors. For example, they can rely on internal and external analyst forecasts, or on timing information from market makers' order books (Chae, 2005). In addition, some retail investors lack information on the impact of this timing on structured product payoffs. For instance, the ex-dividend date is relevant to this payoff but not the dividend announcement, payment, or record date. In this section, we exploit a discontinuity in issuers' dividend timing information advantage to support our second hypothesis.

4.1 Intuition behind the RD approach

A structured product investor is not entitled to receive the underlying's dividend that accrues during the lifetime of a product, i.e., product payoffs are defined on the underlying's ex-dividend price. A discrete dividend before product maturity then reduces the investor's final payoff of a structured product. Thus, even a minor misjudgement of future ex-dividend dates can have a large impact on perceived product values. Specifically, if an investor expects the ex-dividend date to occur after product maturity but the underlying actually goes ex-dividend before or at maturity, he or she obtains the product payoff based on the ex-dividend share price instead of cum-dividend.[15] Therefore, retail investors may overvalue a product if they have incomplete dividend timing information and the future ex-dividend date occurs shortly before product maturity (just–before products). Such overvaluation cannot occur if the future ex-dividend date occurs shortly after product maturity (just–after products). In this case, investors would undervalue a structured product if they misjudge the ex-dividend date to occur before product maturity.[16] Thus, issuers can use their informational advantage on dividend timing to push overpriced securities to investors with just–before products but not with just–after products.

This discontinuity in issuers' informational advantage at product maturity is quantitatively important for product IPs. For instance, consider product A with a maturity of one year, one discrete dividend payment of 1.5%, an ex-dividend date one day after maturity, a Delta of one, and an IP equal to our sample's average of 1.48%. An otherwise identical product B with a maturity that is just one day shorter than that of product A

[15] A share starts trading ex-dividend in the opening of an ex-dividend date, but a structured product matures at closing.

[16] If investors were to believe, mistakenly, that the ex-dividend date would occur after the future ex-dividend date, this misjudgment would have no impact on their product valuation as both dates occur after product maturity.

has around a 1.5% lower replication price (ignoring discounting). Thus, if retail investors misjudge the future dividend date of product B to be one or more days later, such that they are ready to pay the same issue price as for product A, product B's IP doubles to $1.48\% + 1.5\% = 2.98\%$ compared with product's A IP of 1.48%. Whereas issuers double their proceeds with product B, however, investors attain a less attractive product. Specifically, the 1.5% lower replication price of product B implies that, on average, investors attain a 1.5% smaller investment performance with product B than with product A.

4.2 RD approach and results

We now exploit the discontinuity in issuers' informational advantage regarding dividend timing information around product maturity dates to investigate the impact of imperfect information on an outcome variable that captures product performance. To this end, we closely follow the standard regression discontinuity (RD) approach in Chang et al. (2014).

We define our assignment variable as the difference between the closest expected ex-dividend date and the product maturity date expressed in days. The closest expected ex-dividend date is the product underlying's expected ex-dividend date that is nearest to product maturity. We estimate expected ex-dividend dates by projecting the historical ex-dividend dates in the year prior to the initial fixing date of a product into future years.[17] A negative (positive) value of the assignment variable indicates that the expected ex-dividend date occurs before (after) the maturity date. A product with a negative or zero assignment variable (a just–before product) is treated because issuers have an exploitable informational advantage with respect to dividend timing. A product with a positive assignment variable is non-treated (a just–after product). We expect the treated products to be more overpriced compared than the non-treated products.

We use unexplained product performance (UP) as a measure of structured products'

[17]Ex-dividend dates are usually relatively stable. The mean deviation from the previous year's date in our sample is only seven days.

initial overpricing to retail investors. The outcome variable UP is the fraction of a product's ex-post performance that is not explained by the performance of its underlying. We use UP as an overpricing measure because higher overpricing, i.e., higher IPs, leads to inferior unexplained product performance for investors. In our main analysis, we do not use IP directly as the outcome variable. The calculation of IPs is based on replication prices that depend on our own projection of expected dividend dates (see the Appendix). Thus, potential ex-dividend date projection errors could lead to spurious correlations between treatment assignment and the outcome variable IP. Such errors may even cause discontinuities in the outcome variable around the threshold and, hence, could drive our conjecture from the RD design. In contrast, UP is independent of how we calculate initial replication prices and, thus, cannot exhibit any discontinuity around the threshold due to dividend projection errors. Thus, we proceed by using UP as the outcome variable in the main RD design.[18]

To obtain UPs, we collect the residuals of the regression

$$\begin{aligned} &Product\,Performance_i = \alpha + \beta_1 Return\,Underlying_i + \\ &\beta_2 Product\,Category_i + \beta_3 Return\,Underlying_i\,x\,Product\,Category_i + \epsilon_i, \end{aligned} \tag{3}$$

where $Product\ Performance$ is the annualized ex-post performance of product i calculated as the return between the issue price and the final payoff and *Return Underlying* is the annualized ex-post total return of the underlying of product i multiplied by delta. Multiplying the underlying return by *Delta* accounts for the property in virtue of which structured products have differing sensitivities to their underlyings. As alternative product categories exhibit diverse payout profiles, we also incorporate *Category*, which captures the product category of product i, and its interaction with *Return Underlying*. We present the regression output in Table 5. With an R-squared of 90%, the regression

[18] Using IP yields very similar results. Figure A2 in the Appendix, for example, confirms that treated products exhibit a discontinuously larger IP compared to non-treated products.

model reflects the variation in $Product\ Performance$ very well. The residuals of Eqn. (3) exhibit a standard deviation of 0.093. We use these residuals as our outcome variable UP. A low UP indicates high initial overpricing. UP, however, could also be affected by a misspecification of the pricing model in Eqn. (3). We mitigate this concern in two ways. First, we apply alternative pricing model specifications. Second, we measure the UP differences between treated and non-treated products within the RD approach and, thus, systematic misspecifications should cancel out.

INSERT TABLE 5 NEAR HERE

Figure 1 depicts UPs around the threshold. We fit a linear function on either side of the threshold using binwidths of 5 and 10. Each bin represents the average of either 5 or 10 observations.[19] The discontinuity in UPs at the threshold implies that just–before products experience discontinuously lower unexplained product performance than just–after products.

INSERT FIGURE 1 NEAR HERE

If the variation in the treatment near the threshold is approximately randomized, just–before and just–after products should differentiate only with respect to issuers' informational advantage. To ensure randomization around the threshold in our application, issuers should not be able to completely manipulate the difference between ex-dividend and maturity dates (McCrary, 2008). We provide statistical and intuitive practical evidence along three dimensions that this randomization condition of the assignment variable is satisfied in our setting. First, we test the randomization condition with the standard manipulation test based on McCrary (2008) and find no discontinuity in the density function of the assignment variable around the threshold (t-statistics of 0.76).

Second, Figure 2 shows that banks issue structured products throughout the year. Around 80% of ex-dividend dates in our sample, however, occur in the dividend season

[19]The number of observations per bin can vary if there is an unusually high or low number of observations on a given day.

during March, April, or May. Thus, issuers would have to considerably deviate from standardized maturities (0.5, 1, 1.5, 2, 2.5 or 3 years) with products issued in June, July, August, December, January, or February to create just–before products by manipulating their maturities. We find, however, that 76% of products issued in these month have standardized maturities, which is even larger than the 70% of products with standardized maturities issued in March, April, May, August, September, or October.

Finally, we plot products' time to maturity around the RD threshold in Figure 3. Most products have a maturity of one year or just less than one year because products with a maturity beyond one year are subject to the stamp tax in Switzerland. Whereas issuers could manipulate the just–after products with a one-year maturity on the right-hand side of the threshold to become just–before products by simply increasing their maturity by a few days, such manipulated products would lose their tax advantage. As almost no dots on the right-hand side of the threshold are slightly above the one-year maturity line, Figure 3 implies that issuers abstain from such manipulation. This example also illustrates that exogenous reasons for product maturities such as taxes prevent issuers from completely manipulating the assignment variable.

INSERT FIGURE 2 NEAR HERE

INSERT FIGURE 3 NEAR HERE

We now apply a fuzzy RD design to establish a causal relationship between issuers' informational advantage and the degree of product overpricing. We use a fuzzy RD approach because, at product initiation, issuers have estimated future ex-dividend dates but not realized ex-dividend dates and, hence, do not know with certainty whether a product is treated. To explore the discontinuity in issuers' informational advantage around product maturity dates, we use our projected ex-dividend dates as an instrument for the actual ex-post realized ex-dividend dates. Following Chang et al. (2014), we employ a two-stage least-squares approach. As we have no prior on the functional relationship between our assignment variable and the outcome variable, we use a local polynomial of order one to construct the point estimator.[20]

The first-stage regression model is

$$Ex\,Post_i = \alpha_1 + \beta_1 Days_i + Ex\,Ante_i[\alpha_2 + \beta_2 Days_i] + \epsilon_i, \tag{4}$$

where $Ex\ Post_i$ is a dummy equal to one if the actual (ex-post) ex-dividend date closest to the maturity date occurred after product maturity and zero otherwise. $Days_i$ is the difference between our projected ex-dividend date closest to the maturity date and the maturity date measured in days. $Ex\ Ante_i$ is a dummy equal to one if our projected ex-dividend date occurred after product maturity and zero otherwise. We present the regression output in Table 6.

INSERT TABLE 6 NEAR HERE

We apply the fitted values from Eqn. (4) as an instrument for $ExPost_i$ in the second-stage regression. The second-stage regression model is

$$UP_i = \alpha_1 + \beta_1 Days_i + \widehat{Ex\,Post}_i[\alpha_2 + \beta_2 Days_i] + \epsilon_i, \tag{5}$$

where UP_i is the outcome variable, $\widehat{Ex\,Post}_i$ is the predictor for $Ex\ Post_i$ estimated in Eqn. (4), and α_2 is the coefficient of discontinuity at the threshold. If issuers push overpriced products to retail investors when their informational advantage is higher, α_2 should be positive.

The RD design requires the specification of a bandwidth determining the number of observations on either side of the threshold. We follow the rule-of-thumb bandwidth calculation presented in Lee and Lemieux (2010). The optimal bandwidths of the UPs requires 86 observations on the left-hand side and 51 observations on the right-hand side

[20] The results are also robust for local polynomials of order two or higher.

of the threshold, respectively. These bandwidths correspond to a time window of [-19, 19] days around the maturity date.

The results of the second-stage regression are presented in Table 7. We find a positive and significant discontinuity in UP of 10.1% at the threshold between treated and non-treated products with a t-statistic of 2.18. This discrete jump represents 1.1 times the one-standard-deviation change in UPs. According to our RD design, just–before and just–after products should differentiate in issuers' informational advantage only around the threshold. Thus, the upward jump implies that issuers increase the price of products when they have an informational advantage over investors.

Table 7 also reports the coefficients and t-statistics of the second-stage regression for all cut-offs in a six-week time window around our assignment variable threshold of zero. As expected, days around zero are significant. From all remaining cut-offs, only day six exhibits a marginally significant discontinuity. This result confirms that the discontinuity is important only around our threshold.

INSERT TABLE 7 NEAR HERE

To further verify the RD assumption of local randomization, we investigate whether observable variables also exhibit discontinuities around the threshold. To this end, we repeat our RD approach but replace UP_i in Eqn. (5) with the respective variable. A significant jump/drop of alternative variables besides UP at the threshold could mean that the just–before products used in our RD approach differ discontinuously from just–after products along other dimensions than the informational advantage, which could drive our main finding. The results are presented in Table 8. We find no significant discontinuity for most observable variables. Only $Delta$ is marginally significant and positive. This jump, however, tends to reduce UP for just–after products compared with just–before products (see Eqn. 3) and, hence, works against finding a positive discontinuity in UP. Another caveat is that the discontinuity in UP could be driven by a discontinuity in the underlyings' return. We observe, however, no discontinuity for *Underlying Return*. We further test whether the time to maturity of just–before products deviates more often from standardized time to maturities compared with just–after products. We measure *Deviation* as the absolute distance between the structured products' time to maturity and the closest standardized time to maturity (0.5, 1, 1.5, 2, or 3 years) in years. A negative coefficient would indicate that issuers deviate more often from standardized maturities before than after the threshold to manipulate product maturities. More frequent deviations could imply a non-randomization of treatment around the threshold. We find, however, no significant discontinuity.

INSERT TABLE 8 NEAR HERE

Overall, our RD approach confirms our conjecture of Section 3.2 that issuers particularly overprice products when their informational advantage is larger.

5 Product design and imperfect information

In this section, we examine whether issuers also structure products towards their informational advantage. To this end, we employ a matched-sample approach to compare the informational advantage of underlyings that are chosen for a product with otherwise similar underlyings that are not chosen. This approach allows us to reduce the bias due to confounding variables and, thus, increases the validity of our results.

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

For each underlying that is actually chosen for a structured product, we then select five underlyings from the available set that are the closest neighbors with respect to the square root of the sum of squared distances weighted by the inverse sample covariance (the Mahalanobis distance). As matching variables, we use the control variables suggested by Henderson and Pearson (2011), the index of the underlying, and the corresponding industry based on the two-digit Standard Industrial Classification (SIC) code. The majority of products, namely 579 out of the 1012, are issued on underlyings listed in the Swiss Market Index (SMI). Furthermore, 292 products are constructed with underlyings that belong to the EuroStoxx 50 Index. We assign the remaining 141 product underlyings to the category "Other". As launching a product takes some time due to the design, planning, and subscription period, we lag the matching variables by up to three weeks.

Finally, we compute the difference between the value of $Higher\ Vola$ ($Higher\ Div$) of the actually chosen underlying and the average value of $Higher\ Vola$ ($Higher\ Div$) of the matched underlyings. We perform one-sided t-tests to analyze whether this difference is significantly above zero. Our findings are presented in Table 9.

INSERT TABLE 9 NEAR HERE

In Column (1) we lag the matching variables by one week. The results show that chosen underlyings have significantly more $Higher\ Vola$ and $Higher\ Div$ dummies equal to one than comparable available underlyings. Quantitatively, the differences imply that the probability of having a higher implied than historical volatility is 2.3% higher with chosen than with available underlyings, whereas that of having a higher expected than historical dividend is 6% higher. As shown in Columns (2) and (3), the results are also significant if we lag the matching variables by two and three weeks. Thus, after controlling for exogenous factors that can influence issuers' product underlyings choices, we find that issuers tend to select underlyings for which they have a stronger informational advantage regarding volatility and dividends.

6 Robustness

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

6.1 Robustness of overpricing results

In Tables 10 and 11, we discuss alternative specifications of the main regressions in Tables 3 and 4.

INSERT TABLE 10 NEAR HERE

INSERT TABLE 11 NEAR HERE

To incorporate a potential non-linear relationship between volatility or dividend and IP, we also consider the square product of $Impl\ Vola$ ($Impl\ Vola\ Squared$) and $IBES$ $Dividend$ ($IBES\ Div\ Squared$) into our regression model. The Columns (1) in both tables show that our results remain qualitatively unchanged.[21]

A systematic error in the calculation of $Impl\ Vola$ could introduce a correlation between the independent variable IP and the control variable $Impl\ Vola$ or $Higher$ $Vola$ because some structured products entail options (used to calculate the IP via the replication price) with maturity and strike that are close to those of the extracted control variable $Impl\ Vola$. 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 trading days to define the controls $Impl\ Vola$ 182 and $Higher\ Vola$ 182 in our regressions. Whereas this implied volatility should still proxy for future expected volatility, none of our structured products is replicated with a 182 trading days at-the-money put option. Column (2) in Table 10 shows that our results are robust to this specification.

[21] $Impl\ Vola\ Squared$ has a negative coefficient but the point estimate of implied volatility is positive for the entire implied volatility distribution in our sample.

In Column (3) of Table 10 and Column (2) of Table 11, we replace our explanatory dummies with continuous variables. *Vola Difference* is the difference between *Impl Vola* and *Hist Vola*. *Div Difference* is the difference between *IBES Div* and *Hist Div*. The coefficients of both variables are positive and significant. Thus, products with larger volatility and dividend informational advantages exhibit, on average, higher *IPs*.

A potential concern with our results is that they are driven by issuers' installing higher *IPs* for certain product categories. A correlation of the unobserved heterogeneity on the product category level with at least one of the main explanatory variables could bias our conclusion. The same problem arises if certain issuers tend to require higher *IPs* than others. Thus, we rerun the regressions with product category and issuer fixed effects. Our results are robust to this alternative specification, as shown in Column (4) of Table 10 and Column (3) of Table 11.

Another objection to our findings is that the coefficients of the informational advantage proxies could be affected by cross-sectional heterogeneity of underlyings or correlated standard errors within underlying clusters. To address this concern, we also include underlying fixed effects and clustered standard errors at the underlying level in Column (5) of Table 10 and Column (4) of Table 11. Our results are robust to this specification.

Next, we include a battery of additional control variables that could affect our results in Column (6) of Table 10 and Column (5) of Table 11. We incorporate *Hist Vola* and *Hist Div*, respectively, to account for the concern that the results for our informational proxies *Higher Vola* and *Higher Div* could be driven by the historical information. For example, issuers may increase *IPs* when *Hist Vola* or *Hist Div* is low.

The degree of competition in the structured products market may also affect issuers' *IP* decision. In a more competitive market, for example, competitors' price decisions could exert price pressure on the issuer. Thus, we incorporate the $HH-Index$ as an additional control. $HH-Index$ is the Herfindal-Hirshman-Index calculated based on the market shares of issuers in the number of products at each date. A higher value indicates a more monopolistic market.[22]

Structured products may also serve banks as a medium-term funding source. Thus, issuers' funding needs can influence their product pricing behavior. We control for $Funding\ Needs$ with the quarterly ratio between deposit and total assets of each issuer.

Because investors face the default risk of the issuer when investing in a structured product, issuers may need to compensate investors for this risk (Arnold et al., 2016). Hence, the IP could depend on the issuer's creditworthiness. Thus, we incorporate the issuer's $CDS\ Spread$ as a proxy for default risk. This spread is interpolated to the product's maturity.

The economic environment also influences the market conditions under which structured products are issued. We include the values of 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-on-month growth rate of Switzerland's GDP and aims to indicate the Swiss business cycle.

Issuers might face opportunity costs from issuing products with longer maturities. Therefore, we also control for a product's $Time\ to\ Maturity$. We also 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 ($Short-term\ Product$).

Following the idea of Célérier and Vallée (2017) that complexity affects IPs, we also incorporate a proxy for complexity. As in Célérier and Vallée (2017) we define complexity as the number of features contained in a product's payoff formula ($Features$). The idea behind this proxy is that the valuation of products with more features is more complex.

Another potential concern with the volatility result is that the IP is driven by the possibility that retail investors demand a different volatility risk premium than institutional investors. In Table 10, we therefore include $VSMI$, which is an index based on implied volatilities of SMI options across maturities, to control for time variation in the

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

volatility risk premium.

Our result of a significant role of informational advantage proxies for explaining IPs is robust to these additional controls. In addition, the coefficient of $Higher\ Vola$ is negative and significant. Thus, IPs are also driven by historical volatility information.[23] The negative and significant coefficient of $CDS\ Spread$ indicates that products of issuers with higher default risk exhibit lower IPs. As expected, products with a longer $Time\ to\ Maturity$ exhibit larger IPs. The positive and significant coefficient of $Features$ confirms the positive relationship between complexity and IPs in Célérier and Vallée (2017).[24] The remaining control variables are not statistically significant.

6.2 Robustness of regression discontinuity approach

Our RD results are robust to alternative methodologies and specifications.

As structured products entail derivative components, their return is not linearly related to the underlying. Therefore, we rerun the regression model 3 by including the quadratic term of *Return Underlying* and its interaction with *Product Category*. The jump at the threshold remains statistically significant.

Following the suggestion of Imbens and Lemieux (2008), we also investigate the sensitivity of our results to the bandwidth choice. Thus, we repeat the RD analysis by considering multiples of the baseline bandwidths. The discontinuity is robust to alternative bandwidths definitions. For example, if we double (triple) the number of observations on both sides of the threshold, the coefficient is equal to 9.77% (4.92%). As expected, the magnitude of the coefficient declines and significance vanishes for very large multiples because just–before products with a wide distance between their ex-dividend date and the maturity date become just–after products in terms of the previous ex-dividend date

[23] If we include $Hist\ Vola$ as a control variable, the model exhibits considerable multicolinearity measured by the Variance Inflation Factor. The coefficient of $Higher\ Vola$ remains positive and significantly positive if we exclude $Hist\ Vola$ from the model in Column (6).

[24] Alternative complexity measures yield similar results.

(and vice versa).

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

7 Conclusion

We present evidence that the overpricing and design of structured products are driven by specific information sources over which issuers enjoy an informational advantage compared with retail investors. In particular, we show that products with a volatility information advantage for issuers have an approximately 64% larger overpricing than without this advantage, and products with a dividend information advantage for issuers have a 53% higher overpricing. Consistent with the hypothesis that issuers exploit their informational advantage, overpricing is larger for products with a higher value sensitivity to the corresponding information source, a higher cost to retail investors of accessing information, and a larger portion of less-sophisticated investors. The power of the informational advantage channel to explain overpricing is important statistically and economically, whereas standard proxies for the production cost of structured products, the market environment, or liquidity are mostly insignificant. Our results imply that issuers' volatility and dividend information advantages have important explanatory power for the existence and cross-sectional variation of product overpricing. We also show that banks design products towards the information friction sources that we identify. This design result is a concern for systemic stability because it suggests that financial engineers actively contribute to imperfect information in the financial system.

There is a vigorous ongoing debate on the caveats of financial innovation such as product complexity and investor sophistication (e.g., Carlin, 2009; Zingales, 2015; Célérier and

Vallée, 2017). We contribute to this discussion with evidence that unequal access to information is an additional important caveat of financial innovations. Our results imply that the current product disclosure policy is insufficient to prevent financial engineers from exploiting their informational advantage over investors. The Dodd-Frank Act, for instance, only broadly suggests that adequate information should be given to investors. Hence, information exploitation appears to have largely escaped regulators in charge of investor protection. As we find that financial engineers have a tendency to design products of which investors are incompletely informed and because of the concern that this incomplete information causes market fragility (Rajan, 2006; Gorton and Metrick, 2012; Stein, 2012; Gennaioli et al., 2012), desirable regulatory policies should aim at mitigating this information friction. By identifying the specific information sources through which financial engineers exploit their informational advantage over investors, our study is useful by guiding this policy debate along two dimensions. First, it helps to decide which type of information should be publicly disclosed. For example, we show that improving investors' access to implied volatility information reduces issuers' exploitation of their volatility information advantage. Second, it allows policy makers to evaluate and incorporate in their decision the conclusion of the disclosure literature that depending on the information type, publicly disclosing more information can benefit or harm welfare (Bond and Goldstein, 2015; Goldstein and Yang, 2017). The content and exact form of such information provision regulations seem fruitful directions for future research.

Appendix: Replication prices

Each structured product is replicated by using fixed-income and option components.

Discount Certificates (DC) are replicated as

$$DC = \frac{M}{exp(rT)} - P(S - PV(D), M, T, \sigma_P), \tag{6}$$

where M is the redemption amount of the bond component, r is the interest rate, T is the time to maturity of the product, 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 dividend payments predicted by IBES to occur during the lifetime of a product. σ_P is the implied volatility of the put option with corresponding strike and maturity.

We replicate a Barrier Discount Certificate (BDC) as

$$BDC = \frac{M}{exp(rT)} + C(S - PV(D), Y, T, \sigma_C) - DIP(S - PV(D), X, B, T, \sigma_{DIP}), \tag{7}$$

where M is the redemption value of the bond component, r is the interest rate, T is the time to maturity of the product, $C(S - PV(D), Y, T, \sigma_C)$ is a call option on the underlying of the product with strike Y, time to maturity T, and implied volatility σ_C, and $DIP(S - PV(D), X, B, T)$ 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}.

Reverse Convertibles (RC) are replicated by

$$RC = \frac{N}{exp(rT)} + \sum_{t_i \leq T} \frac{c_{t_i}}{exp(rt_i)} - \alpha P(S - PV(D), X, T, \sigma_P), \tag{8}$$

where N denotes the nominal amount, t_i is the coupon payment dates, c_{t_i} is 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 a certificate.

We replicate Capped Outperformance Certificates (COC) as

$$\begin{aligned} COC = &\frac{M}{exp(rT)} - P(S - PV(D), M, T, \sigma_P) + \\ &(\alpha - 1)C(S, Y, T, \sigma_{C1}) - (\alpha - 1)C(S - PV(D), M, T, \sigma_{C2}), \end{aligned} \tag{9}$$

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}. $C(M, T)$ is a call option with strike M.

Barrier Reverse Convertibles (BRC) are replicated by

$$BRC = \frac{N}{exp(rT)} + \sum_{t_i \leq T} \frac{c_{t_i}}{exp(rt_i)} - \alpha DIP(S - PV(D), X, B, T, \sigma_{DIP}), \tag{10}$$

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

Finally, we construct Bonus Certificates (BC) with

$$\begin{aligned} BC = &\frac{M}{exp(rT)} + C(S - PV(D), M, T, \sigma_C) - \\ &P(S - PV(D), M, T, \sigma_P) + \alpha DOP(S - PV(D), M, B, T, \sigma_{DOP}), \end{aligned} \tag{11}$$

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

σ_{DOP}.

We obtain the option components in a replication price by transforming traded (American) EUREX option prices into the (European) option prices of the structured product. For an accurate transformation, we need the expected 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 expected dividend entry prior to the initial fixing date to forecast the dividend amount paid during a product's lifetime. We obtain expected ex-dividend dates by projecting historical ex-dividend dates within a year prior to the initial fixing of a product into the future.

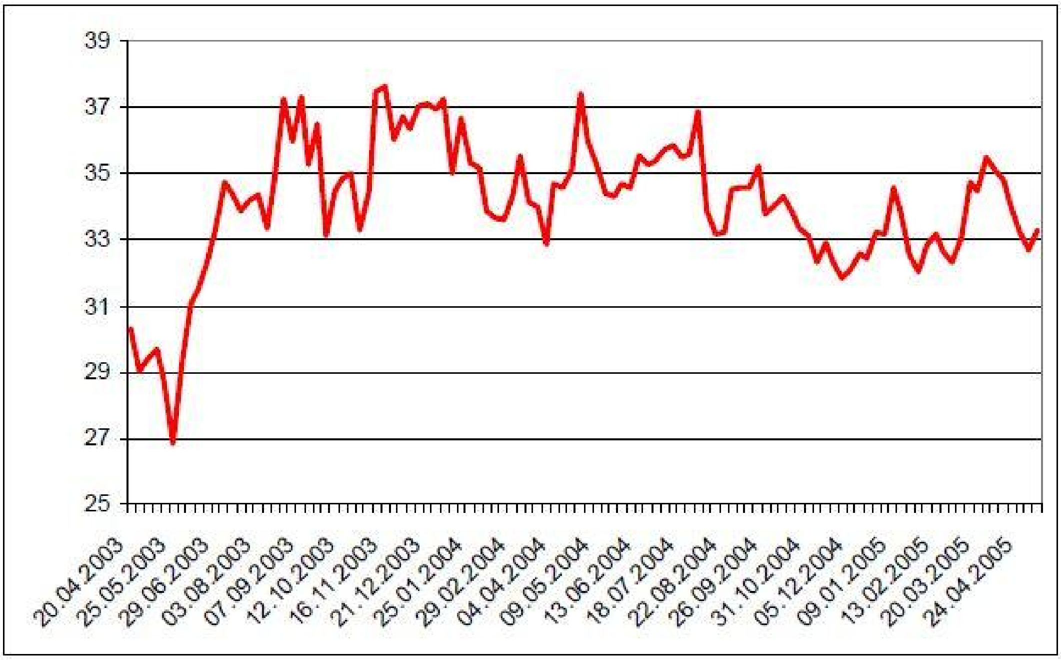
We extract implied volatilities from traded EUREX options. For each option contained in a structured product, we identify four corresponding EUREX options: one with the closest lower strike price and closest longer maturity, another with the closest lower strike price and closest shorter maturity, a third with the closest higher strike price and closest longer maturity, and a fourth 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 by 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 observed EUREX option settlement price. Subsequently, we bilinearly 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.

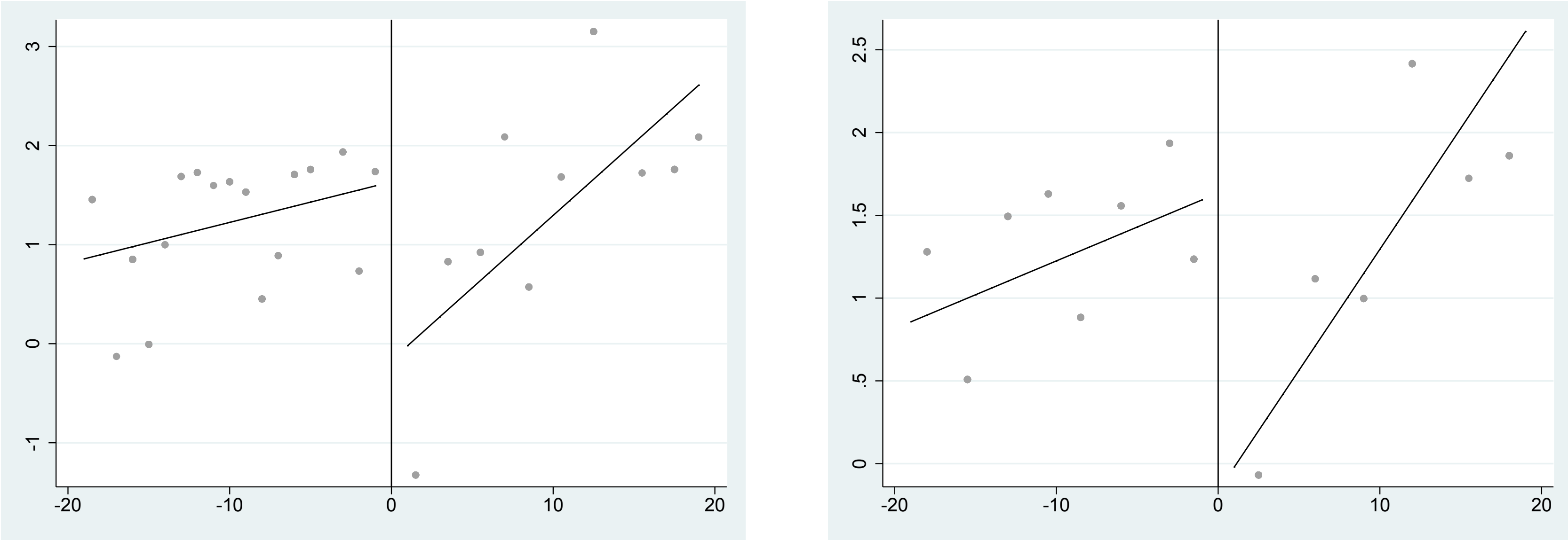
For the interest rate, r, we follow the literature by using interpolated London Interbank Offered Rates (LIBOR) in the currency of the structured product for different maturities (Henderson and Pearson, 2011). For maturities beyond twelve months, we apply the corresponding swap rates. As the maturity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

Because structured products in our sample entail only options of the European type, we apply the Black-Scholes formula to price the plain vanilla options contained in a product. Barrier options are calculated by using the formula of Hull (2009) for knock-in and knock-out options. We incorporate the estimated 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 that are expected to occur during a product's lifetime.

Figure A1: Historical Price Evolution

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





(a) Binwidth = 5

(b) Binwidth = 10

Figure A2: Issue Premium

This figure shows the distribution of the issue premium (IP) in a time window of [-19, 19] days around the maturity date. The projected dividend payment date is defined as the difference between the expected ex-dividend date and the maturity date in days. A negative (positive) value indicates that the ex-dividend date is expected to occur before (after) the maturity date. A low (high) IP indicates relatively attractive (unattractive) products. We fit a linear function on either side of the threshold using binwidths of 5 and 10. Each bin represents the average of either 5 or 10 observations.

References

An, Xudong, Yongheng Deng, and Gabriel Stuart, 2011, Asymmetric information, adverse selection, and the pricing of cmbs, *Journal of Financial Economics* 100, 304–325.

Arnold, Marc, Dustin Schuette, and Alexander Wagner, 2016, Neglected risk in financial innovations: Evidende from structured product counterparty exposure, *Unpublished Working Paper* .

Ashcraft, Adam B., and Til Schuermann, 2008, Understanding the securitization of subprime mortgage credit, *Federal Reserve Bank of New York Staff Report No.318* .

Battalio, Robert H., and Richard R. Mendenhall, 2005, Earnings expectations, investor trade size, and anomalous returns around earnings announcements, *Journal of Financial Economics* 77, 289–319.

Baule, Rainer, Oliver Entrop, and Marco Wilkens, 2008, Credit risk and bank margins in structured financial products: Evidence from the German secondary market for discount certificates, *Journal of Futures Markets* 28, 376–397.

Benet, Bruce A., Antoine Giannetti, and Seema Pissaris, 2006, Gains from structured product markets: The case of reverse-exchangeable securities (RES), *Journal of Banking & Finance* 30, 111–132.

Bhattacharya, Nilabhra, 2001, Investors' trade size and trading responses around earnings announcements: An empirical investigation, *The Accounting Review* 76, 221–244.

Bhattacharya, Nilabhra, Ervin L. Black, Theodore E. Christensen, and Richard D. Mergenthaler, 2007, Who trades on pro forma earnings information?, *The Accounting Review* 82, 581–619.

Bhattacharya, Utpal, Andreas Hackethal, Simon Kaesler, Benjamin Loos, and Steffen Meyer, 2012, Is unbiased financial advice to retail investors sufficient? Answers from a large field study, *The Review of Financial Studies* 25, 975–1032.

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

Bond, Philip, and Itay Goldstein, 2015, Government intervention and information aggregation by prices, *Journal of Finance* 70, 2777–2811.

Bouveret, Antoine, Ricardo Crisóstomo, Monica Gentile, Victor Mendes, Paulo Pereira da Silva, and Fernando Silva, 2013, Economic report: retailisation in the EU, *European Securities and Markets Authority* .

Burth, Stefan, Thomas Kraus, and Hanspeter Wohlwend, 2001, The pricing of structured products in the Swiss market, *Journal of Derivatives* 9, 30–40.

Calonico, Sebastian, Matias D. Cattaneo, and Rocio Titiunik, 2014, Robust nonparametric confidence intervals for regression-discontinuity designs, *Econometrica* 82, 2295–2326.

Campbell, John, 2006, Household finance, *Journal of Finance* 61, 1553–1604.

Carlin, Bruce, and Gustavo Manso, 2011, Obfuscation, learning, and the evolution of investor sophistication, *The Review of Financial Studies* 24, 754–785.

Carlin, Bruce I, 2009, Strategic price complexity in retail financial markets, *Journal of Financial Economics* 91, 278–287.

Carr, Peter, and Liuren Wu, 2016, Analyzing volatility risk and risk premium in option contracts: A new theory, *Journal of Financial Economics* 120, 1–20.

Célérier, Claire, and Boris Vallée, 2017, Catering to investors through security design: Headline rate and complexity, *The Quarterly Journal of Economics* 132, 1469–1508.

Chae, Joon, 2005, Trading volume, information asymmetry, and timing information, *Journal of Finance* 60, 413–442.

Chang, Yen-Cheng, Harrison Hong, and Inessa Liskovich, 2014, Regression discontinuity and the price effects of stock market indexing, *The Review of Financial Studies* 28, 212–246.

Choi, James, David Laibson, and Brigitte Madrian, 2009, Why does the law of one price fail? An experiment on index mutual funds, *The Review of Financial Studies* 23, 1405–1432.

Coval, Joshua, Jakub Jurek, and Erik Stafford, 2009, The economics of structured finance, *Journal of Economic Perspectives* 23, 3–25.

Cox, John, Stephen Ross, and Mark Rubinstein, 1979, Option pricing: A simplified approach, *Journal of Financial Economics* 7, 229–263.

Daniel, Kent, David Hirshleifer, and Siew H. Teoh, 2002, Investor psychology in capital markets: Evidence and policy implications, *Journal of Monetary Economics* 49, 139–209.

DeMarzo, Peter, 2005, The pooling and tranching of securities: A model of informed intermediation, *The Review of Financial Studies* 18, 1–35.

Gennaioli, Nicola, Andrei Shleifer, and Robert Vishny, 2012, Neglected risks, financial innovation, and financial fragility, *Journal of Financial Economics* 104, 452–468.

Goldstein, Itay, and Liyan Yang, 2017, Good disclosure, bad disclosure, *Working Paper* .

Gorton, Gary, and Andrew Metrick, 2012, Securitized banking and the run on repo, *Journal of Financial Economics* 104, 425–451.

Hanson, Samuel G., and Adi Sunderam, 2013, Are there too many safe securities? Securitization and the incentives for information production, *Journal of Financial Economics* 108, 565–584.

Henderson, Brian J., and Neil D. Pearson, 2011, The dark side of financial innovation: A case study of the pricing of a retail financial product, *Journal of Financial Economics* 100, 227–247.

Hull, John C., 2009, *Options, Futures, and Other Derivatives* (Pearson, Prentice Hall).

Imbens, Guido W., and Thomas Lemieux, 2008, Regression discontinuity designs: A guide to practice, *Journal of Econometrics* 142, 615–635.

Lee, David S., and Thomas Lemieux, 2010, Regression discontinuity designs in economics, *Journal of Economic Literature* 48, 281–355.

McCrary, Justin, 2008, Manipulation of the running variable in the regression discontinuity design: A density test, *Journal of Econometrics* 142, 698–714.

Piskorski, Tomasz, Amit Seru, and James Witkin, 2015, Asset quality misrepresentation by financial intermediaries: Evidence from the RMBS market, *The Journal of Finance* 70, 2635–2678.

Rajan, Raghuram G., 2006, Has finance made the world riskier?, *European Financial Managment* 12, 499–533.

Schiller, Robert, 2003, *The new financial order: Risk in the 21st century* (Princeton University Press).

Sirri, Erik R., and Peter Tufano, 1998, Costly search and mutual fund flows, *The Journal of Finance* 53, 1589–1622.

Stein, Jeremy C., 2012, Monetary policy as financial-stability regulation, *The Quarterly Journal of Economics* 127, 57–95.

Stoimenov, Pavel A., and Sascha Wilkens, 2005, Are structured products fairly priced? An analysis of the German market for equity-linked instruments, *Journal of Banking and Finance* 29, 2971–2993.

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* .

SVSP, Schweizerischer Verband für Strukturierte Produkte, 2013, Marktreport Strukturierte Produkte, *Quartalsbericht* .

Swiss Bankers Association, 2011, Wealth management in Switzerland: Status report and trends, *Basel* .

Zingales, Luigi, 2015, Presidential address: Does finance benefit society?, *The Journal of Finance* 70, 1327–1363.

Table 1
Overview of Structured Products Sample

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

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

Table 2
Descriptive Statistics

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

	N	Mean	Std. Dev.	Q25	Median	Q75
Issue Premium	1012	1.48	2.09	0.52	1.35	2.24
Impl Vola	1012	28.67	11.26	21.27	26.18	33.95
Hist Vola	1012	31.24	18.59	18.85	24.40	36.69
Higher Vola	1012	0.56	0.50	0	1	1
IBES Div	1012	0.03	0.02	0.01	0.03	0.04
Hist Div	1012	0.04	0.06	0.01	0.02	0.04
Higher Div	1012	0.60	0.49	0	1	1
Market Cap	1012	3.80	1.09	3.26	4.08	4.70
3m Excess Return (x100)	1012	1.46	11.09	-5.26	1.35	8.44
12m Excess Return (x100)	1012	0.87	21.26	-11.48	0.18	12.75
1m Turnover	1012	7.45	1.92	6.15	8.21	8.98
3m Turnover	1012	8.55	1.91	7.24	9.27	10.06
1m Call Option Volume	1012	2.63	3.79	0.31	1.66	3.13
1m Put Option Volume	1012	2.55	3.41	0.33	1.66	3.27
Vega	1012	-0.46	0.29	-0.49	-0.43	-0.39
Delta	1012	0.02	0.18	0.01	0.01	0.02
IVolatility	1012	0.76	0.43	1	1	1
Trading Size	783	10.71	1.15	9.98	10.68	11.33
Features	1012	2.12	0.90	1.00	2.00	3.00
Impl Vola Squared	1012	9.49	8.40	4.52	6.85	11.52
Impl Vola 182	994	31.19	14.73	21.65	28.32	37.46
IBES Div Squared (x100)	1012	0.12	0.17	0.01	0.06	0.15
Time to Maturity (trading days)	1012	294.16	150.80	249	255	265

Table 3
OLS Regressions of the Issue Premiums for Volatility Measures

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

VARIABLES	(1) IP	(2) IP	(3) IP	(4) IP	(5) IP
Impl Vola	4.879***	4.071***	3.768***	4.102***	4.570***
	(6.41)	(5.37)	(4.98)	(5.41)	(6.28)
Higher Vola		0.951***	0.553**	1.343***	3.469***
		(6.35)	(2.18)	(5.08)	(3.01)
Vega			1.056***		
			(3.93)		
Higher Vola × Vega			-0.745*		
			(-1.70)		
IVolatility				0.151	
				(0.72)	
Higher Vola × IVolatility				-0.508*	
				(-1.77)	
Trading Size					0.006
					(0.07)
Higher Vola × Trading Size					-0.246**
					(-2.28)
Features					
Market Cap	0.164**	0.122*	0.115	0.127*	0.113
	(2.24)	(1.69)	(1.61)	(1.75)	(1.59)
3m Excess Return	0.793	1.119*	1.229**	1.135*	-0.316
	(1.29)	(1.85)	(2.04)	(1.88)	(-0.52)
12m Excess Return	-0.432	-0.422	-0.398	-0.450	-0.033
	(-1.34)	(-1.34)	(-1.27)	(-1.42)	(-0.10)
1m Turnover	0.185	-0.090	-0.082	-0.066	0.334
	(0.64)	(-0.32)	(-0.29)	(-0.23)	(1.20)
3m Turnover	-0.221	0.065	0.062	0.039	-0.334
	(-0.76)	(0.23)	(0.22)	(0.13)	(-1.18)
1m Call Option Volume	-1.673	-0.659	-0.447	-0.351	-3.640
	(-0.49)	(-0.20)	(-0.13)	(-0.10)	(-0.84)
1m PutOption Volume	3.754	3.291	2.868	3.222	6.731
	(0.98)	(0.88)	(0.77)	(0.86)	(1.48)
Constant	0.020	-0.867	-0.319	-0.938*	-0.576
	(0.04)	(-1.62)	(-0.58)	(-1.68)	(-0.56)
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1,012	1,012	1,012	1,012	783
R-squared	0.133	0.167	0.180	0.170	0.147

Table 4

OLS Regressions of the Issue Premiums for Dividend Measures

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

VARIABLES	(1) IP	(2) IP	(3) IP	(4) IP
IBES Div	6.751**	-0.549	-0.080	-6.905**
	(2.14)	(-0.16)	(-0.02)	(-1.97)
Higher Div		0.783***	0.360**	3.269***
		(5.22)	(2.02)	(2.74)
Delta			-22.548***	
			(-4.57)	
Higher Div × Delta			26.074***	
			(3.90)	
Trading Size				0.065
				(0.73)
Higher Div× Trading Size				-0.244**
				(-2.22)
Impl Vola	5.260***	5.935***	6.314***	5.774***
	(6.74)	(7.60)	(8.12)	(7.64)
Market Cap	0.145*	0.092	0.100	0.107
	(1.96)	(1.25)	(1.37)	(1.48)
3m Excess Return	0.785	0.851	0.672	-0.348
	(1.28)	(1.40)	(1.12)	(-0.56)
12m Excess Return	-0.319	-0.445	-0.478	-0.183
	(-0.98)	(-1.38)	(-1.50)	(-0.56)
1m Turnover	0.218	0.204	0.239	0.510*
	(0.76)	(0.72)	(0.85)	(1.83)
3m Turnover	-0.249	-0.222	-0.250	-0.504*
	(-0.86)	(-0.78)	(-0.88)	(-1.78)
1m Call Option Volume	-1.120	-0.524	-1.116	-4.225
	(-0.33)	(-0.16)	(-0.33)	(-0.96)
1m Put Option Volume	2.765	1.987	2.597	6.820
	(0.72)	(0.52)	(0.69)	(1.48)
Constant	-0.106	-0.546	-0.319	-0.927
	(-0.20)	(-1.03)	(-0.60)	(-0.83)
Year FE	Yes	Yes	Yes	Yes
Observations	1,012	1,012	1,012	783
R-squared	0.137	0.160	0.178	0.133

Table 5
OLS Regression of the Unexplained Performance

This table presents results using an OLS regression. The dependent variable is *Product Performance*, which is the annualized ex-post performance of a structured product calculated as the return of the final payoff over the issue price. *Return Underlying* is the annualized ex-post total return of the underlying of a product multiplied by *Delta*. We use Product Category fixed effects and the interaction between them and *Return Underlying*. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) Product Performance
Return Underlying	0.879***
	(9.35)
Product Category FE	Yes
Product Category FE Interaction	Yes
Observations	1012
R-squared	0.900

Table 6
Fuzzy RD Design: First-Stage Regression

This table presents the first-stage regression from a Fuzzy RD Design. The dependent variable is *ExPost*, a dummy that is equal to one if the actual (ex-post) dividend payment date closest to the maturity date occured after product maturity, and zero otherwise. *Days* is calculated as the difference between the estimated ex-dividend date closest to the maturity date and the maturity date measured in days. *ExAnte* is a dummy equal to one if the estimated ex-dividend date closest to the maturity date occured after product maturity, and zero otherwise. We apply optimal bandwidths based on the rule-of-thumb approach. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) Ex-Post
Days	0.001
	(0.12)
Ex Ante	0.688***
	(5.77)
Days x Ex Ante	0.005
	(0.43)
Observations	137
R-squared	0.554
F	57.40

Table 7
Fuzzy RD Design: Second-Stage Regression

This table presents results of the Fuzzy RD Design using a two-stage least-squares approach with local polynomials of order one. First, we use dividend payment date projections to instrument the actual ex-post outcome based on Eqn. (4). Second, we use the fitted values from the first-stage regression as an instrument in Eqn. (5). The dependent variable is the unexplained performance measure (UP), which is defined as the residuals of the model estimated with Eqn(3). We apply optimal bandwidths based on the rule-of-thumb approach. We report the coefficients of discontinuity α_2 estimated in Eqn. (5) for thresholds at various cut-offs in a time window of six weeks around day 0. The thresholds are defined as the differences between the estimated ex-dividend date closest to the maturity date and the maturity date measured in days. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	-15	-14	-13	-12	-11	-10	-9	-8
α_2	-0.099	-0.010	0.010	0.015	-0.014	0.047	0.081	-0.021
	(-0.56)	(-0.13)	(0.21)	(0.35)	(-0.30)	(0.55)	(1.14)	(-0.31)
N	163	161	163	160	157	149	149	151
	-7	-6	-5	-4	-3	-2	-1	0
α_2	-0.014	-0.031	0.200	0.072	0.225	0.108*	0.097**	0.101**
	(-0.29)	(-0.49)	(1.00)	(0.67)	(1.53)	(1.68)	(1.99)	(2.18)
N	149	149	140	139	136	142	141	137
	1	2	3	4	5	6	7	8
α_2	0.086	0.077	-0.158	-0.094	-0.011	-0.159*	-0.197	-0.158
	(1.29)	(0.99)	(-1.30)	(-0.60)	(-0.11)	(-1.67)	(-1.60)	(-1.16)
N	136	132	131	122	116	118	118	118
	9	10	11	12	13	14	15	
α_2	-0.168	-0.148	-0.063	-0.047	0.091	0.119	0.190	
	(-1.47)	(-1.37)	(-0.33)	(-0.41)	(0.78)	(1.07)	(1.65)	
N	118	114	109	103	102	99	93	

Table 8
Validity Test: Control

This table presents the RD design validity test for observable control variables using a two-stage least-squares approach with local polynomials of order one. The standard controls are defined in Table 4. *Return Underlying* is the annualized ex-post total return of the underlying. *Deviation* is defined as the absolute distance between the time to maturity of a structured product and its closest standardized time to maturity (0.5, 1, 1.5, 2, or 3 years) in years. We apply optimal bandwidths based on the rule-of-thumb approach. We report the coefficients of discontinuity α_2 estimated in Eqn. (5). t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	IBES Div	Hist Div	Higher Div	Delta
α_2	0.011	0.050	-0.085	0.017*
	(0.92)	(1.12)	(-0.32)	(1.70)
N	137	137	137	137

	Trading Size	Features	Impl Vola	Market Cap
α_2	0.181	-0.699	-0.062	0.506
	(0.27)	(-1.55)	(-1.12)	(0.93)
N	99	137	137	137

	3m Excess Return	12m Excess Return	1m Turnover	3m Turnover
α_2	-0.078	-0.084	0.040	-0.006
	(-1.41)	(-0.63)	(0.05)	(-0.01)
N	137	137	137	137

	1m Call Option Volume	1m Put Option Volume	Return Underlying	Deviation
α_2	0.006	0.006	-0.035	0.037
	(0.36)	(0.35)	(-0.19)	(1.01)
N	137	137	137	137

Table 9
Nearest Neighbor Matching

This table presents results of the Nearest Neighbor matching approach. For each underlying that is actually chosen for a structured product, five non-chosen underlyings that are closest neighbors with respect to the Mahalanobis distance are selected. The matching variables are the index and industry of an underlying, 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. Depending on the specification of the model, the matching variables are lagged by one, two, and three weeks. *Corresponding Index* is the index of the underlying. We define *Industry* as the two-digit SIC code. *Higher Vola* (*Higher Div*) is a binary variable that is equal to one if *Impl Vola* (*IBES Div*) is larger than *Hist Vola* (*Hist Div*), and zero otherwise. *Mean Difference Higher Vola* (*Mean Difference Higher Div*) is calculated as the difference between the value of *Higher Vola* (*Higher Div*) of the underlying that is actually chosen and the mean value of *Higher Vola* (*Higher Div*) of the matched underlyings. 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.

	(1)	(2)	(3)
Corresponding Index	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Market Cap	Yes	Yes	Yes
3m Excess Return	Yes	Yes	Yes
12m Excess Return	Yes	Yes	Yes
1m Turnover	Yes	Yes	Yes
3m Turnover	Yes	Yes	Yes
1m Call Option Volume	Yes	Yes	Yes
1m Put Option Volume	Yes	Yes	Yes
Lag	1 Week	2 Weeks	3 Weeks
Mean Difference Higher Vola	0.023**	0.020*	0.022**
	(0.04)	(0.06)	(0.05)
Mean Difference Higher Div	0.060***	0.058***	0.062***
	(0.00)	(0.00)	(0.00)

Table 10
Robustness Tests: Volatility Measures

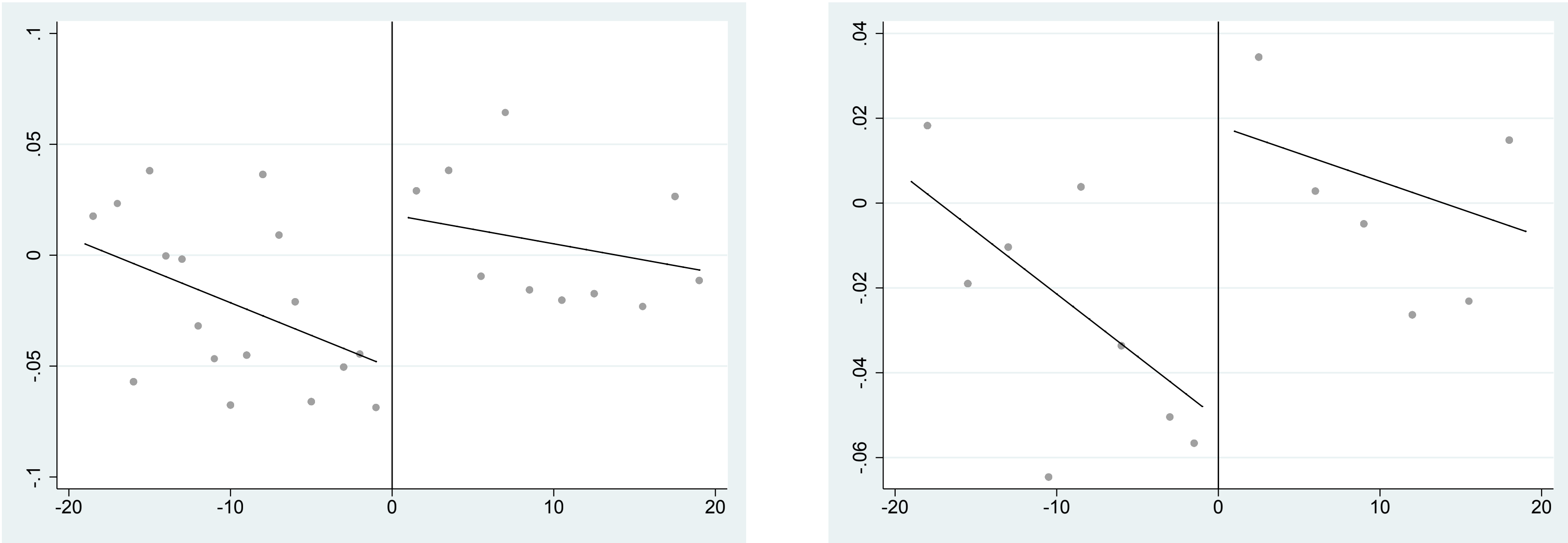
This table presents various robustness tests for our main findings. The dependent variable is the Issue Premium (IP), which is the issue price of a structured product minus its replication value, scaled by the issue price, expressed in percentage points. $Higher\ Vola$ is a binary variable that is equal to one if $Impl\ Vola$ is larger than $Hist\ Vola$, and zero otherwise. $Impl\ Vola\ Squared$ is calculated as the square product of $Impl\ Vola$. $VSMI$ is an index based on implied volatilities of SMI options across maturities. $Higher\ Vola$ 182 is a binary variable that is equal to one if $Impl\ Vola$ 182 is larger than $Hist\ Vola$, and zero otherwise. $Impl\ Vola$ 182 is the annualized implied volatility of an at-the-money put option on the product's underlying with a maturity of 182 days. $Vola\ Difference$ is calculated as the difference between $Impl\ Vola$ and $Hist\ Vola$. $HH-Index$ is defined as the Herfindal-Hirshman-Index calculated based on the market shares of the firms in the number of products on the initial fixing date. We calculate $Funding\ Needs$ as the quarterly ratio between deposit and total assets. $CDS\ Spread$ is the CDS spread of the issuer at the initial fixing date. We use the Economic Barometer published by the KOF Swiss Economic Institute as a proxy for $Economic\ Environment$. $Time\ to\ Maturity$ is measured in years. $Short-term\ Product$ is a binary variable that is equal to one if $Time\ to\ Maturity$ is smaller or equal to 1 year, and zero otherwise. $Features$ is defined as the number of different features contained in a product's payoff formula based on the typology of features proposed by Célérier and Vallée (2017). We include the same standard control variables as in Table 3. We control for year fixed effects. Depending on the specification of the model, we additionally control for product category, issuer, and underlying fixed effects. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) IP	(2) IP	(3) IP	(4) IP	(5) IP	(6) IP
Impl Vola	16.698***		4.245***	5.381***	3.920**	13.269***
	(5.86)		(5.69)	(7.59)	(2.40)	(10.11)
Higher Vola	0.858***			1.072***	0.872***	0..688***
	(5.74)			(7.91)	(4.43)	(4.08)
Impl Vola Squared	-16.581***					
	(-4.59)					
Impl Vola 182		-0.456				
		(-0.79)				
Higher Vola 182		0.711***				
		(4.34)				
Vola Difference			5.791***			
			(7.49)			
Hist Vola						-6.653***
						(-7.01)
VSMI						-0.035**
						(-2.22)
HH-Index						3.069
						(1.15)
Funding Needs						-2.678
						(-1.26)
CDS Spread						-0.431**
						(-2.05)
Economic Environment						0.004
						(0.33)
Time to Maturity						0.388*
						(1.95)
Short-term Product						-0.023
						(-0.08)
Features						0.387***
						(4.48)
Constant	-2.853***	0.948*	-0.195	-0.101	0.562	-1.837
	(-4.17)	(1.80)	(-0.38)	(-0.16)	(0.22)	(-1.19)
Standard Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Product Category FE	No	No	No	Yes	No	No
Issuer FE	No	No	No	Yes	No	No
Underlying FE	No	No	No	No	Yes	No
Underlying Cluster SE	No	No	No	No	Yes	No
Observations	1,012	994	1,012	1,012	1,012	851
R-squared	0.184	0.114	0.179	0.360	0.282	0.311

Table 11
Robustness Tests: Dividend Measures

This table presents various robustness tests for our main findings. The dependent variable is the Issue Premium (IP), which is the issue price of a structured product minus its replication value, scaled by the issue price, expressed in percentage points. $Higher\ Div$ is a binary variable that is equal to one if $IBES\ Div$ is larger than $Hist\ Div$, and zero otherwise. $IBES\ Div\ Squared$ is calculated as the square product of $IBES\ Div$. $Div\ Difference$ is defined as the difference between $IBES\ Div$ and $Hist\ Div$. $HH-Index$ is the Herfindal-Hirshman-Index calculated based on the market shares of the firms in the number of products on the initial fixing date. We calculate $Funding\ Needs$ as the quarterly ratio between deposit and total assets. $CDS\ Spread$ is the CDS spread of the issuer at the initial fixing date. We use the Economic Barometer published by the KOF Swiss Economic Institute as a proxy for $Economic\ Environment$. $Time\ to\ Maturity$ is measured in years. $Short-term\ Product$ is a binary variable that is equal to one if $Time\ to\ Maturity$ is smaller or equal to 1 year, and zero otherwise. $Features$ is defined as the number of different features contained in a product's payoff formula based on the typology of features proposed by Célérier and Vallée (2017). We include the same standard control variables as in Table 4. We control for year fixed effects. Depending on the specification of the model, we additionally control for product category, issuer, and underlying fixed effects. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) IP	(2) IP	(3) IP	(4) IP	(5) IP
IBES Div	-3.353	5.425*	-1.140	6.443	1.847
	(-0.37)	(1.73)	(-0.37)	(1.13)	(0.49)
Higher Div	0.800***		0.345**	0.763***	0.326**
	(5.06)		(2.47)	(4.03)	(2.04)
IBES Div Squared	36.597				
	(0.33)				
Div Difference		4.487***			
		(4.42)			
Hist Div					-1.146
					(-1.10)
HH-Index					0.651
					(0.23)
Funding Needs					-3.216
					(-1.43)
CDS Spread					-0.513**
					(-2.55)
Economic Environment					-0.008
					(-0.61)
Time to Maturity					0.490**
					(2.29)
Short-term Product					-0.042
					(-0.14)
Features					0.295***
					(3.20)
Impl Vola	5.910***	5.674***	6.522***	6.822***	7.616***
	(7.53)	(7.28)	(8.84)	(4.29)	(8.52)
Constant	-0.526	-0.185	0.600	0.708	0.240
	(-0.99)	(-0.35)	(0.90)	(0.26)	(0.15)
Standard Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Product Category FE	No	No	Yes	No	No
Issuer FE	No	No	Yes	No	No
Underlying FE	No	No	No	Yes	No
Underlying Cluster SE	No	No	No	Yes	No
Observations	1,012	1,012	1,012	1,012	851
R-squared	0.160	0.154	0.324	0.290	0.217



(a) Binwidth = 5

(b) Binwidth = 10

Figure 1
Unexplained Performance

This figure shows the distribution of the unexplained performance (UP) in a time window of [-19, 19] days around the maturity date. The projected dividend payment date is defined as the difference between the expected ex-dividend date and the maturity date in days. A negative (positive) value indicates that the ex-dividend date is expected to occur before (after) the maturity date. UP is calculated as the residual of regression Eqn. (3). We fit a linear function on either side of the threshold using binwidths of 5 and 10. Each bin represents the average of either 5 or 10 observations.

Figure 2
Product Issuances throughout the Year

This figure depicts the number of products issued per month. Month number 1 is January, number 2 is February and so forth.

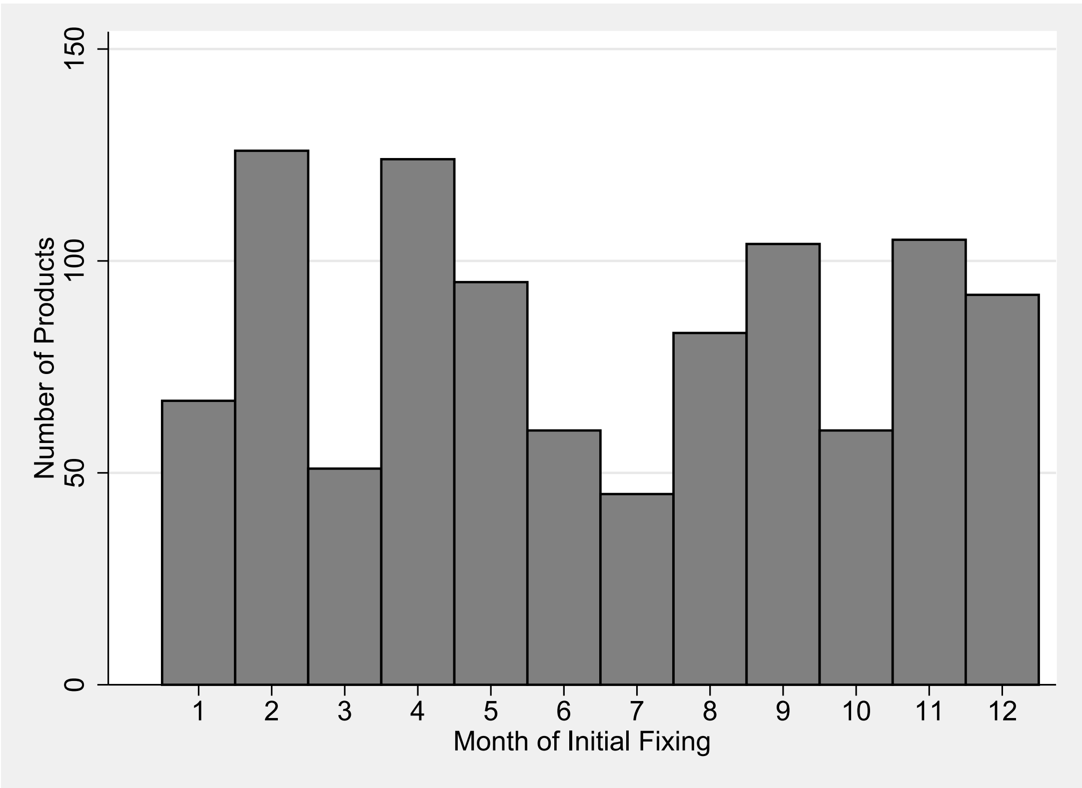


Figure 3
Time to Maturity

This figure shows the distribution of time to maturity in a time window of [-19, 19] days around the maturity date. The projected dividend payment date is defined as the difference between the expected ex-dividend date and the maturity date in days. A negative (positive) value indicates that the ex-dividend date is expected to occur before (after) the maturity date. The time of maturity is calculated in years. Solid dots indicate products with a time to maturity of one year or shorter and hollow dots products with a time to maturity of longer than one year.