THE MOTIVES FOR FINANCIAL COMPLEXITY: AN EMPIRICAL INVESTIGATION *

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Abstract

This paper investigates, by analyzing a large market of investment products targeted exclusively at households, the motives for financial complexity. We develop a robust measure of complexity via a text analysis of the term sheets of 55,000 retail structured products issued in 17 European countries since 2002. We find the complexity of structured products to have significantly increased over the period 2002-2010. Calculating the fair value of a subsample of products, we show that relatively more complex products have higher markups, and that the headline rate offered by a product is an increasing function of its complexity. We further show that distributors, such as savings banks, that target low-income investors offer relatively more complex products. Lastly, we find that competition amplifies rather than mitigates migration towards higher complexity. These findings are difficult to fully reconcile with a completing market motive for financial complexity, being more consistent with banks catering to yield seeking investors or developing obfuscation strategies.

Keywords: Financial Complexity, Household Finance, Structured Products, Obfuscation

JEL codes: I22, G1, D18, D12

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1 Introduction

Financial complexity is one of the key developments of modern finance, and has been pointed out as a catalyst of the recent financial crisis (Caballero and Simsek (2009)). A significant part of the current level of complexity in the financial system results from the development of complex products. The motives for developing complex instruments continue to be debated. Financial complexity may be a corollary to financial innovation aimed at improving risk sharing and better matching investor demand (Allen and Gale (1994)). A growing theoretical literature has, however, rationalized a darker side of financial complexity manifested in banks offering products overly complex relative to the level of investor understanding or with the intent of developing local monopolies (Gabaix and Laibson (2006), Ellison (2005), Carlin (2009)). The current paper extends this inquiry by investigating the motives for financial complexity empirically.

We focus on one large category of investment products broadly marketed to households worldwide, specifically, the retail market for structured products. This market presents an ideal laboratory for our investigation because, (1) the financial complexity of retail structured products, as well as *ex ante* cost of complexity to the retail investor, can be objectively measured, and (2) the issue of complexity is more critical in household finance owing to the relative unsophistication of retail investors (Lusardi et al. (2013), Lusardi et al. (2010)). Typically structured with derivatives, retail structured products include any investment products marketed to retail investors that possess a payoff defined *ex ante* by a formula over a given underlying.[1] This market currently encompasses, in Europe alone, more than one trillion dollars in assets under management.

The present study establishes a series of empirical facts that begin to shed light on the motives for financial complexity. We first document the complexity of retail structured products to have increased over time, with no discernable decrease during the financial crisis. We then show the exposures embedded in these complex products to have evolved

[1]This market includes, for example, capital-protected products structured by combining zero coupon bonds with a call option on a given index.

over time, with an increasing share exposed to downside risk during the financial crisis. We next document that more complex products yield higher markups to the banks that distribute them. These *ex ante* higher markups translate to lower *ex post* performance for more complex products. We further show that more complex products offer a higher headline rate than simpler products, and that the characteristics of financial institutions affect the complexity of the products they offer. Entities that target low income investors offer more complex products than institutions that target wealthier investors, and banks with relatively lower funding costs offer relatively more complex products. Lastly, we find that increased competition amplifies rather than mitigates evolution towards increasing financial complexity, which effect also generates a higher level of product differentiation in the market.

The development of a robust and replicable measure of financial complexity is an important contribution of the present paper. Our methodology aims to capture the multidimensionality of contracts offered in the retail market for structured products, the rationale being that the more dimensions it has, the more difficult a product is for the retail investor to understand and compare with other products. We first develop a typology that identifies all possible dimensions of structured products, and within each dimension all possible features that the payoff formula may possess. We then calibrate and run a text analysis algorithm that scans the textual description of the final payoff formula for 55,000 products in a novel dataset. The algorithm infers from each feature embedded in each payoff formula the number of dimensions of each product. This constitutes our complexity index. We also provide two parsimonious measures of complexity, length of the text description of the payoff, and number of scenarios that result from the payoff formula.

Our dataset contains detailed information on all retail structured products sold in Europe since 2002, which total 1.4 trillion euros of issuance. These products are available, in European countries, to any household from a local bank.[2] Key database characteristics that facilitate the empirical investigation of financial complexity include coverage of 17

[2]European regulation does not limit access to accredited investors, as is the case in the United States.

countries, nine years of data with strong inter-country and inter-temporal heterogeneity, inclusion of more than 400 distributors, and, at the issuance level, product characteristics, such as information on distributors and volume sold. Most important, the dataset provides us with a detailed textual description of the payoff formula translated into English based on the same stable methodology used for years. [3]

We confront the results from our empirical investigation to different motives for offering complex products. Our stylized facts are hard to reconcile with the view that they are offered to complete markets for households. Low income investors are unlikely to be most in need of complex exposures, and the evolution of embedded exposures is unlikely to be driven by investor risk appetite. The design of retail structured products is more consistent with banks catering to demand for high yield instruments in a low interest rate environment. Our results also strongly suggest an obfuscation motive. Financial complexity has increased over the years, but the financial sophistication of retail investors remains low, and that more complex products offer higher markups to distributing banks suggests a link between complexity and greater profitability. Lastly, competition appears to amplify rather than mitigate complexity. Intensified competition, whether in the form of increased numbers of competitors or entry of a potential substitute product (Exchange Traded Funds, or ETF), induces greater complexity.

Our work contributes to several strands of the literature. First, our paper builds on the theoretical literature that models product complexity. Ellison (2005) and Gabaix and Laibson (2006) describe how inefficient product complexity arises in a competitive equilibrium. Carlin (2009) and Carlin and Manso (2011) develop models in which the fraction of unsophisticated investors increases endogenously with product complexity, the former showing product complexity to increase as competition intensifies. Our paper tests the direct implications of these models by empirically assessing the role of competition in the evolution of financial complexity.[4] More generally, our work contributes to the emerging

[3] http://www.structuredretailproducts.com/.

[4] Sun (2014) empirically tests the effect of competition on price discrimination against consumers with low price sensitivity.

literature on complex securities (Griffin et al. (2014), Ghent et al. (2014), Carlin et al. (2013), Amromin et al. (2013), Sato (2014)).

Our work also contributes to the literature on the role of financial literacy and limited cognition in consumer financial choice and bank strategies. Bucks and Pence (2008) and Bergstresser and Beshears (2010) explore the relationship between cognitive ability and mortgage choices, and Lusardi and Tufano (2009) find lower financial literacy to be associated with poorer financial decisions. Complexity might amplify these issues. The present paper also complements recent interest in the advisory role financial intermediaries play for their retail clients (Anagol et al. (2013), Bergstresser and Beshears (2010), Hackethal et al. (2012), Karabulut (2013)), and reports evidence consistent with the salience theory of investment and reaching for yield phenomenon (Bordalo et al. (2012), Bordalo et al. (2013)).

Our paper contributes as well to the literature on structured products. The finding of Hens and Rieger (2014) that the most popular structured products do not bring additional utility to rational investors suggests that these products are not introduced with the objective of completing markets. Empirical studies of the retail market for structured products have focused on pricing issues, Henderson and Pearson (2011), for example, on the basis of a detailed analysis of 64 issues of a popular type of product, estimating overpricing by banks to be nearly 8%.

In terms of policy implications, our work stresses the importance of considering product complexity independently of risk.[5] An additional step may be to impose a cap on complexity, or to promote standardization of financial products. Such actions presume the development and utilization by regulators of a comprehensive and homogeneous measure of product complexity such as the one developed here.[6]

Our paper proceeds as follows. Our methodology for measuring the complexity and markup of retail structured products is detailed in Section 2. In Section 3, we report the

[5]The French Authority of Market Regulation considers product complexity only when capital is at risk.

[6]Limiting certain investment opportunities to qualified investors who meet an income/asset threshold, as is done in the United States, might be another regulatory option.

results of our empirical investigation and evaluate market trends, product returns, and the competitive environment. In Section 4, these results are discussed in light of possible motives for the development of complex products. Our conclusions are presented in Section 5.

2 Measuring Financial Complexity

The retail market for structured products is an ideal laboratory in which to study motives for financial complexity. With assets under management close to one trillion dollars, the market is undeniably large, but more important, the financial complexity of retail structured products, as well as *ex ante* cost of complexity to the retail investor, can be objectively measured. In this section, we provide background on this market and explanations of the data used and methodology developed to measure complexity and calculate product markups.

2.1 The Retail Market for Structured Products

A. Background

Retail structured products include any investment products marketed to retail investors with a payoff that follows a formula defined ex ante. Typically being structured with embedded options, these products leave no room for discretionary investment decisions during the life of the investment.[7] Although based mainly on equity indices and individual stocks, these products also offer the possibility of exposure to commodities, fixed income, or other alternative indices. Our study excludes products like ETFs, the payoffs of which are a linear function of a given underlying index.

Below is an example of a product Banque Postale, the French Post Office Bank, offered in 2010.

[7] Retail structured products, unlike mortgages, provide no discretion to the investor in terms of exercising options, which is done automatically.

Vivango is a 6-year maturity product whose final payoff is linked to a basket of 18 shares (largest companies by market capitalization within the Euro Stoxx 50). Each year, average performance of the three shares that perform best relative to their initial levels is recorded and the shares are removed from the basket for subsequent calculations. At maturity, the product offers guaranteed capital of 100%, plus 70% of the average of the performances recorded annually throughout the investment period.

This example illustrates the high complexity of a mass market structured product. The product complexity contrasts with the low level of financial sophistication likely posessed by the average Banque Postale client. Both the state-contingent nature of the underlying index and the concept of averaging performance across time make the product difficult to assess.

The retail market for structured products emerged in Europe in the mid-1990s and has subsequently experienced steady growth. The approximately 700 billion euros invested in European retail structured products in 2011 represents nearly 3% of all European financial savings, or 12% of mutual fund assets under management. With a market share of 64%, and 357 distributors in 2010, Europe is by far the largest market for these products. But the US and Asian markets are growing fast. Issues of retail structured product in the US market since 2010 exceed USD 200 billion.[8] Differences in regulation, in terms of both consumer protection and bank supervision, are likely the main explanation for the difference in size between the European and US markets. US consumer protection laws require a high minimum investment by individuals in retail structured products, on the order of USD 250,000. Additionally, until its repeal in 1999, the Glass Steagall Act limited the internal structuring of such products. The predominance of personal brokers over bank employees as financial advisers may also have played a role in delaying development of this market in the United States.

Growing demand for passive products, fueled by increasing skepticism about the added

[8] Source: Euromoney Structured Retail Products.

value of active management, is among the drivers of the retail market for structured products (Jensen (1968), Grinblatt and Titman (1994)). The high profitability enjoyed by the banks that structure and distribute retail structured products has also played an important role in the growth of this market (Henderson and Pearson (2011)). Additional markups, on top of disclosed fees, are hidden in the product by structuring banks, which can typically replicate the relevant payoff structure at a cost below the price offered to retail investors. In Europe, paradoxically, the 2007 Markets in Financial Instruments (MiFID) regulation that requires distributors to disclose commercial and management fees may have elevated the incentive to hide markup within financial products.

The structuring process largely shapes the organization of the retail structured products market. The products are structured by a few large banks that have the exotic trading platforms needed to create them, but technological barriers being low on the distribution side, distributors are much more dispersed and often distinct from the structuring banks. Retail structured products are consequently marketed by a wide range of financial institutions, from commercial and savings banks to insurance companies to organizations active in wealth management and private banking.[9] Competition thus plays out on two levels: between structuring entities that sell to distributors, and between distributors that sell to retail investors.

The regulatory framework is an important dimension of this market, in which bank supervision and investor protection coexist. Protection of retail investors, to which European regulators have been increasingly attentive, is a pillar of the regulatory framework as defined by the UCITS Directives (1985, 2001, 2011). These directives, however, have focused mainly on disclosure requirements, and may have amplified issues of asymmetric information between distributors and retail investors by requiring disclosures, such as backtesting, that are too abundant or overly technical. Some national regulators, moreover, appear to conflate complexity and risk; the French regulator, for instance, in the latest guidelines

[9]Many of the providers that emphasize structuring expertise in their marketing efforts do not, in fact, structure the products; they only select them and engage in back-to-back transactions with entities that can actually manage the market risk.

for structured products (REF 2010), does not limit complexity if performance is floored at zero.

B. Data

Our data source is *Euromoney Structured Retail Products*, a commercial data provider that has collected detailed information on all retail structured products sold in Europe since the inception of the market (1996).[10] Euromoney provides this data to banks active in the market. Cross-validation with practitioner documents and country-level comparisons with other academic studies suggest that the database provides excellent coverage of the industry. [11]

The retail market for structured products is divided into flow, leverage, and tranche products. We focus on the latter, non-standardized products with a limited, typically 4- to 8-week, offer period and fixed maturity date. These products have the largest investor base, most assets under management (90% of total volume), highest average volumes, and greatest heterogeneity in terms of payoffs. We exclude flow products, which are highly standardized with a high number of low volume (sometimes even null) issues, and leverage products, which are highly speculative, pure option products like warrants and turbos.[12] Retail consumers investing in tranche products typically follow a buy-and-hold strategy owing to the significant penalties for exiting prior to maturity. In Europe, as of December 2010, the total volume of outstanding structured tranche products was valued at EUR 704 billion (41,277 products). [13]

The dataset covers all tranche retail structured products issued between 2002 and 2010 in 17 European countries. In addition to key information contained in prospectuses, such as issue date, maturity, and volume, our data includes for each product a precise text

[10] www.structuredretailproducts.com.

[11] For instance, coverage of Danish products is 10% greater than that of a hand-collected dataset for the same market in Jorgensen et al. (2011).

[12] Flow products, which include bonus and discount certificates, are highly popular in Germany, hundreds being issued daily and 825,063 from 2002 to 2010. Their size, however, is only 20,000 euros, on average, compared to 8.8 million euros for the core market we consider.

[13] Including leverage and flow products brings the number of outstanding structured products to 406,037 and volume to EUR 822 billion.

description of the payoff formula. Examples of product term sheets, obtained from our data provider, are included in the online appendix. We converted the 55,000 term sheets into a unique file that we exploit in our analyses.

Table I reports cumulative volumes per country since the market's inception. Italy, Spain, Germany, and France dominate in terms of volume sold, together constituting 60% of the total market. We match this product level data with additional information on providers (Bankscope and hand-collected data), market conditions (Datastream), and macroeconomic country variables (World Bank) at the time of issue.

INSERT TABLE I

Both volume sold and number of distributors in the retail market for structured products have increased since 2002, with a slight decrease since the financial crisis (Figure I and Table II). The market is divided among commercial, private, and savings banks, and insurance companies.

INSERT FIGURE I

2.2 Methodology for Measuring Complexity

The robust and replicable measure of financial complexity developed here is our paper's principal contribution. Our methodology aims at capturing the multidimensionality of the contracts offered in retail structured products, the rationale being that the difficulty of understanding a product and comparing it with other products increases with the number of dimensions.[14]

We first develop a typology of all features that a retail structured product payoff can possibly possess. Features are classified on a tree-like structure, the nodes of which correspond to eight dimensions, each of which requires additional effort on the part of the retail investor to understand the final payoff formula. Figure II displays the dimensions

[14]Studying only the non-linearity of the products' final payoff would overlook important dimensions like path dependence and underlying selection mechanisms.

and corresponding features that comprise our typology. The first, and only compulsory, dimension defines the main structure of the payoff formula. The other dimensions define added features. The frequently added *reverse convertible* feature, for example, which exposes investors to significant underperformance when the underlying falls below a certain threshold, adds an *Exposure Modulation* dimension, inclusion of the *Asian option* feature, which indexes the value of the payoff to the average price of the underlying asset over a certain period of time, a *Path Dependence* dimension. Each of the eight dimensions of our typology including, on average, five mutually exclusive features, our methodology covers more than 70,000 possible combinations of features and, thus, differentiated products. The appendix provides a detailed description of each dimension and definition of each payoff feature.

INSERT FIGURE II

We next calibrate and run for all 55,000 products a text analysis algorithm that scans the textual description of, and identifies and counts each feature contained in, the final payoff formula. The textual description, produced by the data provider, translates into English the minimum information needed to calculate product performance. The algorithm, which looks for specific word combinations that correspond to the features defined in our typology, identifies more than 1,500 different combinations of features and counts the number of features embedded in each payoff formula to measure product complexity. This approach relies on the assumption that all features defined in our typology are of comparable complexity. Given the breadth of the breakdown we develop, the potential error introduced by this assumption, relative to indexes built on a small number of components, is likely to be of minor concern.

Figure III shows how our methodology applies to two products, one arguably more complex than the other. Our algorithm provides the following outputs for these products. The first product payoff incorporates only one feature on the compulsory dimension, *Call*, the second, *Call*, *Himalaya*, and *Asian option*, which relate to the primary, underlying selection, and path dependence dimensions, respectively. The three-dimensionality of the latter product indicates a higher level of complexity. Length of product descriptions also appears to be an increasing function of the number of dimensions.

INSERT FIGURE III

Our methodology enables us to identify and measure the complexity of the payoff formulas of all past and current retail structured products as well as of virtually any new products that might be invented and marketed in the future. Updating the algorithm when new features are created involves only adding a branch to the feature tree. Our methodology also captures complexity in a market characterized by high product diversity. With more than 1,500 different products, a simple typology based on a final product formula with corresponding levels of complexity would not have been adequate, and studying only the non-linearity of the products' final payoff would overlook important dimensions like path dependence and underlying selection mechanisms.

To mitigate potential concerns regarding measurement error, we consider two parsimonious measures of complexity.

The first is the length of the formula description measured in terms of the number of characters. Figure III illustrates how a more complex product requires more text to describe its payoff.

The second alternative measure is the number of scenarios that affect the final return formula. A product payoff might depend on one or several conditions at maturity or during the life of a product. This measure is similar to counting the number of kinks in the final payoff profile, because a change of scenario translates into a point of non-linearity for the payoff function.[15] We quantify the number of scenarios by identifying conditional subordinating conjunctions like "if," "when," and "whether" in the text description of the payoff formula.

Pairwise correlations in the [0.5 - 0.7] range among our three complexity measures suggest coherence and complementarity.

[15]This measure also partially accounts for path dependency, which is not captured by the number of kinks in the final payoff function.

2.3 Methodology for Calculating Markups of Complex Products

To understand the motives for complex products it is necessary to analyze their markups. We define markup as the difference between a retail structured product's issue price and the fair value calculated at issuance. As the fair value calculation requires precise pricing for potentially highly exotic products, we follow industry practice in using a local diffusion model in a Least Squares MonteCarlo setup.

A. Diffusion Model

We estimate the fair value of our sample of retail structured products based on a local volatility diffusion model in which the underlying asset follows the diffusion,

$$\frac{dS_t}{S_t} = r_t dt + \sigma\left(t; S_t\right) dW_t \tag{1}$$

where S_t is the price of the underlying, $\sigma(t; S_t)$ is the volatility surface as a function of maturity and underlying spot price, W_t is a Brownian motion, and r_t is the interest rate.

A local volatility diffusion model, as opposed to a plain-vanilla Black and Scholes formula, is needed to accurately price complex structured products because they frequently have deeply embedded out-of-the-money options, such as an implicit sale of put options or cap on the final payoff.[16] Models of stochastic volatility may improve the accuracy of pricing (Dumas et al. (1998)), but are challenging to calibrate. Moreover, the purpose of our pricing exercise is to identify the price at which structuring banks can replicate the payoff, which they typically assess using local volatility models.

Retail structured product payoffs are largely path dependent. To account for this specificity, we use the Least Squares Monte Carlo (LSM) methodology (Longstaff and Schwartz (2001)) widely recognized and implemented by academics and professionals alike. This approach uses OLS to estimate the conditional expected payoff to the option holder from continuation, which affords a better estimation of the optimal exercise of an American

[16] Henderson and Pearson (2011) and Jorgensen et al. (2011) use constant volatility, but study mainly products with at-the-money options, for which the issue we are discussing is less severe.

option when its value depends on multiple factors.

We enjoyed the support of the Lexifi pricing tool to accurately perform this calculation-intensive methodology, which includes both local volatility diffusion and LSM.[17]

B. Product Sample and Pricing Data

We calculate the markups of 148 retail structured products: the 101 issued in Europe in July 2009 with the Euro Stoxx 50 index as an underlying, and a random sample of 47 products issued in October 2010 with the same underlying.

Restricting our sample in terms of period and underlying maximizes accuracy and within-sample comparability of market conditions. Opting for a sample of products with the same underlying ensures that heterogeneity in complexity and markup derives from the payoff formula and not the underlying assets. The choice of a single index as an underlying requires no assumptions on implied correlation between stocks, as opposed to products linked to a basket of stocks. The Euro Stoxx 50 index, being one of the most liquid financial indexes, is the most frequent underlying asset for the products in our total sample. Euro Stoxx 50 options with various moneyness and maturities trade daily on several exchanges with tight bid-ask spreads.[18] High quality, detailed volatility data is available from Eurex, the largest European derivative exchange.[19] We use the EUR swap rate curve, obtained from Datastream, to discount cashflows. Daily stock prices and historical values of interbank rates (Euribor) are collected from Bloomberg. Finally, we compute from futures prices, also collected from Bloomberg, a constant dividend yield.

Focusing on a relatively short time window ensures comparability of market conditions. We choose July 2009 because the number of issuances and heterogeneity of products linked to Euro Stoxx 50 during that month was the highest recorded since the market's inception.

[17] Deutsche Bank, HSBC, Societe Generale, and Bloomberg are among the many financial institutions that use this tool to price structured products. See www.lexifi.com for details.

[18] Although the fair value does not include transaction costs, an approximation can be obtained by inputting bid or ask quotes instead of mid quotes for the implied volatility. Because options on the Euro Stoxx 50 are highly liquid, this adjustment does not significantly affect the estimates.

[19] Although we use the highest quality implied volatility data available, we cannot account for volatility OTC prices that are likely to have been used in some cases, especially for maturity that exceeds 18 months. Discussions with practitioners suggest that OTC prices or in-house cross-trading typically represent for the bank an improvement over market quotes.

We add products from October 2010 to mitigate concerns regarding the robustness of our analysis over time.

3 Stylized Facts

This section develops from our complexity measure and pricing methodology stylized facts about the cross-section and time series of financial complexity. We look at market global trends, explore heterogeneity at the product and distributor levels, and analyze how the competitive environment within countries affects financial complexity.

3.1 Overall Trends

A. Increase in Financial Complexity

To investigate the year-over-year evolution of financial complexity, we regress the complexity measures on year fixed effects while controlling for a battery of product characteristics, such as type of underlying asset, distributor, format, country, volume, and maturity.

Figure IV, which reports the coefficients of the year fixed effects, shows complexity to have increased significantly over the 2002-2010 period, with almost no decrease during the financial crisis.

INSERT FIGURE IV

The large set of controls in our regression ensures that the increase in financial complexity is not driven by a mechanical compositional effect, such as a country or segment moving in or out of the market. The increase in complexity is robust to conditioning on format, underlying, distributor type, and country fixed effects, as well as on maturity. Our result is also unlikely to result from regulatory change.[20]

[20] We consider the possibility that a change in regulation, specifically, implementation of the MiFID directive on 1 November 2007, might have produced a different methodology for describing payoffs, resulting in measurement error. Our result is immune to this regulation shock for several reasons. First, the text description we use, being extracted from the prospectus and translated by our data-provider based on the

Figure V, which plots the distribution of products from our sample along our complexity index for three sub-periods, shows that the increase is not driven solely by a fraction of the distribution of the complexity. Over time, we observe a decrease in the share of simple, and an increase in the share of the most complex, products. This empirical fact illustrates how banks accumulate new features on existing payoff combinations while progressively removing simpler products from the market.

INSERT FIGURE V

Finally, we provide in the online appendix a figure that plots, using the alternative measures, average complexity over time for the products in our dataset. We observe the same increasing trend over the years covered in our sample, and a comparable magnitude in increase.

B. Evolution of Embedded Exposure

The embedded exposures obtained by the households that invest in this market evolve in parallel with the increase in complexity over the 2002-2010 period.

Table II provides summary statistics on the underlying type, distributor type, marketing format, and volume and design of the products in our dataset. Equity, the most widespread exposure, whether through individual stocks, baskets of stocks, or equity indexes, has decreased slightly over time in favor of other asset classes. In terms of format, structured notes, which bear the credit risk of the issuer and represent a funding tool, are becoming increasingly popular, as opposed to collateralized fund-type products. Products that guarantee at least an investor's initial investment, which dominated at the beginning of the period, are becoming less popular, representing approximately half of product volume in recent years.

INSERT TABLE II

same stable methodology, is not affected by the requirement for additional disclosures, such as backtesting and warnings. Controlling for the time consistency of text descriptions by manually identifying products with identical payoff features both before and after implementation of the MiFID directive, we find that payoff descriptions remain quite similar and include approximately the same numbers of characters.

We focus on the evolution of the share of products that expose investors to downside risk, implicitly selling put options, versus traditional products that offer participation in the upside with a capital protection, implicitly buying call options.

INSERT FIGURE VI

Figure VI plots the share of products with a *reverse convertible* feature that results in investors being exposed to downside risk over the years. The ratio of products with this feature is observed to have increased significantly over the period, and to have remained high during the financial crisis.

3.2 Complexity and Product Returns

A. Markup at Issuance

We use our pricing methodology to investigate the relationship between the complexity of a retail structured product and the size of its markup for the structuring bank. The average estimated markup in our sample is 3.51% not including disclosed entry and management fees, 6.29% including these fees.[21] [22]

We estimate the following cross-sectional regression of product markups on our main complexity proxy,

$$YearlyMarkup_i = \alpha \times \#\ Features_i + \delta_y + \eta_c + \gamma Credit\ Risk_i + \epsilon_i \tag{2}$$

where $YearlyMarkup$ is the difference between issuance price and fair value, estimated as detailed in section 2, normalized by product maturity, $\#Features$ is the number of payoffs embedded in the structured product formula as a measure of its complexity, and X_i is a vector of product level controls. A dummy, $CreditRisk$, indicates non-collateralized

[21]The online appendix provides detailed information on each product we price and the corresponding undisclosed markup we calculate.

[22]Our estimates are slightly lower than those in Henderson and Pearson (2011), and we find 27 products with negative estimated markups. The latter correspond to products, such as bonds and deposits, that provide funding to the issuing bank. To be comparable, we must therefore discount the flows for these products by the banks' funding cost. When we do so, we observe only two cases of negative markups.

products like bonds and deposits. Because these products provide funding to the issuer, this specificity must be taken into account when assessing profitability.[23]

INSERT TABLE III

Table III reports the coefficients of the regression and documents a statistically and economically significant relationship between complexity and markup at issuance.

The first column reports the result of the baseline model. The coefficient on *#Features* is 0.33, significant at the 1% level. That is, adding one additional feature in a payoff formula predicts an increase in the yearly markup of 0.33 percentage points. Retail structured products having an average maturity of 5.5 years, this corresponds to an increase of approximately 1.8 percentage points of the total markup, which amounts to a more than 50% increase in average markup. This result is robust to the complexity measure we use. Adding one additional scenario or one standard deviation variation to the length of the description predicts increases of 0.14 and 0.27 percentage points, respectively, in the yearly markup (see the online appendix).

To ensure that this positive correlation is not driven by the pricing strategy of a limited number of distributors, we introduce distributor fixed effects in column (2), and add fixed effects for all six primary features in column (3), and for the four most frequent discretionary features in column (4). We therefore test that the relationship results from the accumulation of features and not from mispricing of specific features.[24] [25] In column (5), we add disclosed fees to the undisclosed markup and use this aggregated markup as the dependent variable. Column (6) reports results of a robustness check on the asset pricing methodology. We use markups calculated with a fair value obtained using a partial differential equation methodology instead of LSM as a left-hand side variable. The coefficient on our complexity measure *# Features* remains stable and significant in all of these specifications.[26] Although

[23] Arnold et al. (2014) analyze the pricing of credit risk in retail structured products.

[24] There are 35 different issuers in our sample.

[25] Among these, we find that the reverse convertible feature implies a significantly higher markup of 0.7 percentage points.

[26] We obtain a smaller number of observations for column 6 because the path-dependent nature of some products presents a computational challenge.

total fees appear to be correlated with complexity, we note that complexity does not explain disclosed fees only.

B. Ex Post Performance

We examine in this section the relationship between product complexity and *ex post* performance. Although *ex post* performance, because it corresponds to one possible outcome, should be interpreted with caution, this analysis represents an interesting validity test of our previous result. Products' *ex post* performance also enables us to significantly extend our sample via comparison with our pricing exercise. Our database includes the final performance of 48% of the participation products that matured before 2011, which amounts to some 7,500 products.[27] On average, the products in our sample offered a yearly return of 2.44%, 1.3 percentage points lower than the average risk free rate for an equivalent maturity over the same period.

We regress *ex post* performance on our three complexity measures,

$$YearlyPerf_i = \alpha \times \mathit{Complexity}_i + \beta \times \mathit{Capital\ protection}_i + \gamma \mathit{Credit\ Risk}_i + \gamma_a + \delta_y + \eta_c + \epsilon_i \tag{3}$$

where *YearlyPerf* is the yearly return to the investor, namely, the ratio of the total return over product maturity in years, *Complexity* is our complexity measure, and δ_y, η_c, and γ_a are year, country, and underlying asset fixed effects, respectively. To ensure that our results are not driven by different levels of risk associated with different levels of complexity, we include a dummy*, Capital Protection,* that indicates whether the initial capital invested is guaranteed at maturity.

INSERT TABLE IV

Table IV presents the estimated coefficients of the regression for our three measures

[27] Because our data does not include coupon payment realization, we include only products that offer a unique flow at maturity, and thus do not pay any coupon during the life of a product. *Ex post* performance is not available for Germany and Austria.

of complexity. The three specifications indicate a significant negative correlation between product complexity and performance. Adding one payoff feature, or one scenario or one standard deviation, to the length of the payoff description reduces the yearly return by, on average, 0.35 percentage points. This result is both statistically and economically consistent with our previous finding.

C. Headline Rate

We now analyze the headline rate of structured products, defined as the basic rate that results from their primary structure. The headline rate is highlighted in the marketing strategy, as observed in the marketing leaflets included in our data (see the example in the online appendix). We find that more complex products offer a more attractive headline rate.

Structured products are divided into coupon products that pay a coupon at the end of each period, and participation products that offer a fixed participation in the performance of the underlying. We define the headline rate as the coupon offered in the baseline scenario for coupon products, and for participation products as the baseline level of participation in the performance of the underlying. We extract these rates from the product payoff descriptive using a text-analysis algorithm.

We investigate the relationship between the headline rate and level of complexity by regressing the former on the latter using each of our alternative measures and including the usual controls. Table V presents the coefficients of these regressions. The headline rate appears to be positively correlated with level of complexity. Adding one additional feature in the payoff formula is associated with an increase of 0.3 percentage points in the yearly coupon for coupon products, or of 2.3 percentage points in the participation in the underlying performance for participation products. Both relationships are economically significant.

INSERT TABLE V

3.3 Distributor Characteristics and Complexity

A. Distribution Channel

We assess a product's level of complexity according to the type of the marketing bank; savings banks, for example, provide financial services primarily to rural and low- to middle-class households, private banks mainly to high-income individuals. We group distributors into four categories: savings banks, commercial banks, insurance companies, and private banks/wealth managers.[28] Table 1 in the online appendix describes and identifies the types of the 20 main distributor groups in 2010.

Table VI presents statistics on the level of complexity per distributor type. Savings banks that target unsophisticated investors distribute, on average, more complex products than commercial banks, private banks/wealth managers, and insurance companies. We confirm these unconditional statistics by regressing product complexity on distributor type dummies, controlling for product characteristics. The second panel in Table VI shows savings bank products to be significantly more complex than the products of the commercial banks that constitute the control group. Moreover, the coefficient of the savings bank dummy is higher than that of private banks that target significantly wealthier investors.

INSERT TABLE VI

B. Distributor Funding Cost

Turning to the funding costs, which directly affect the interest rate banks can pay on short and long term deposits, we find that banks with high funding costs, which can therefore offer high paying deposits, offer less complex products than banks with lower funding costs.

We regress product complexity on the level of distributors' CDS spread as a proxy for funding cost. We restrict the analysis to banks that have a listed CDS. The CDS spreads used are from Datastream for the period 2007-2010. Table VII displays the regression

[28]For example, German savings banks include Sparkassen (31% market share in 2010) and Volksbanken/Raiffeisenbanken (27% market share in 2010), the main commercial banks are Deutsche Bank (5%) and Commerzbank (3% market share in 2010), and private banks include Sal. Oppenheim (<1% market share in 2010).

coefficients for our three measures of complexity. We include quarter fixed effects to control for changing market conditions. Product complexity appears to be negatively correlated with the level of the distributing bank's CDS spread. Results are robust to using the three measures of complexity.

INSERT TABLE VII

3.4 Country Market Characteristics and Complexity

A. Complexity, Number of Competitors and Market Differentiation

We now examine level of complexity and differentiation relative to the number of competitors in the market. We use panel data at the country and distributor level spanning 15 countries and 471 distributors.[29]

We compute for each country, per year, the number of competitors in the retail market for structured products. To ensure that the identified distributors are independent competitors, we match our data with Bankscope, and regroup distributors by holding companies. We also regroup savings banks of the same network, such as Sparkassen in Germany and Cajas in Spain, because their geographical coverage does not overlap nationally, into the same distributor group. We identify 471 competitors that have been active in the retail market for structured products for one or more years during the 2002-2010 period. We measure market differentiation by counting the number of distinct combinations of features marketed in a given year in a given country.

We then compute a volume-weighted average of financial complexity at the country-year and distributor-country-year levels.[30]

We estimate at the country level the following panel data regression,

$$Y_{c,y} = \alpha + \beta * Competition_{c,y} + \delta_y + \theta_c + \epsilon_{c,y} \tag{4}$$

[29] Two countries, Hungary and Poland, are excluded due to low volume, valued since the market's inception at less than 10 million euros. Norway is not considered due to a ban on selling structured products to retail investors during the 2008-2010 period.

[30] Using equally weighted averages yields comparable results.

where $Y_{c,y}$ is average complexity in columns (1) and (2) and number of product types in columns (3) and (4), and $Competition_{c,y}$ is the number of distributors active in the retail market for structured products in country c and year y. We include country fixed effects, θ_c, to control for time invariant market specificities (e.g., size), and year fixed effects, δ_y, to control for aggregate shocks or common trends in the retail market for structured products. We compute robust standard errors because the low number of observations does not permit satisfactory clustering. Results are displayed in Table VIII.

Column (1) shows level of financial complexity to be positively correlated with number of competitors. A similar estimation at the distributor-country level in column (2), which includes distributor fixed effects, confirms the positive correlation between number of competitors and the complexity of a given distributor's products.[31] This distributor level specification mitigates potential concerns regarding endogenous entries. Examining how distributors adapt relative to the level of competition in the market in which they participate, we observe that offers are adapted to the level of complexity, the same distributor offering relatively more complex products in a relatively more competitive national market. This result suggests that competition contributes to an increase in, rather than mitigates, financial complexity.

We next investigate whether the observed increase in complexity is related to an increase in product diversity. We identify distinct types of products as distinct combinations of payoff features. Using the number of product types sold in country c in year y as a dependent variable in column (3), we find the increase in the number of competitors to be concomitant with greater differentiation of the product offer at the country level. This result suggests the channel through which complexity is increasing over the sample period, namely, banks developing new combinations of features not yet offered in the market, typically by adding a new feature to an existing combination. Migration towards new products leads naturally to an increase in complexity.

INSERT TABLE VIII

[31] We exploit the fact that 51% of providers participate in more than one market.

B. Effects of Competition: ETF Entry Drives Complexity Up

We study the effects on complexity of a shock to the competitive environment, namely, the entry of ETFs. This shock was first used by Sun (2014) to study the price impact of competition on active management investment products in the United States. Using a difference-in-differences set up that exploits the staggered entry of these products in European countries, we find complexity to increase as competition intensifies.

ETFs represent a potential substitute for retail structured products. Both belong to the passive management fund segment. ETFs are simple products, their prices readily observed by sophisticated investors. Linear payoffs make them easy to comprehend, and their cost, which consists of disclosed management fees, is low and easy to observe.

We use two complementary measures for ETF market penetration. We first identify, using Google Trend, when investors' attention turns to these products. We also use Morningstar Direct Data to list and count, by country and year, the total number of ETFs available. Details of these measures are available in the online appendix together with country-level time series.

We estimate at the country-year and distributor-country-year levels the following difference-in-differences model,

$$Y = \alpha + \beta \times ETF_{Awareness} \times Post + \delta_y + \theta_c + \gamma_d + \epsilon_{d,c,y}$$

where Y is average complexity in a given year at the country level in columns (1) to (3), and at the distributor-country level in columns (4) and (5), of Table IX, and $ETF_{Awareness} \times Post$, in columns (1), (2), and (4), is a dummy equal to one when investors in a given country become attentive to ETFs according to Google Trend. In columns (3) and (5), we substitute for $ETF_{Awareness} \times Post$ the number of ETFs listed on a given country's exchange in a given year. More than half of the product distributors being active in several countries, we can include in the specification in columns (4) and (5), in addition to year (δ_y) and country fixed effects (θ_c), distributor fixed effects (γ_d), thereby effectively establishing the difference in complexity of structured products offered by the same distributor when ETFs are, and are not, available as potential substitutes for structured products.

INSERT TABLE IX

We find ETF entries to have a positive and significant impact on the aggregate level of complexity at both country and distributor-country levels for both measures of ETF penetration. Using distributor fixed effects for columns (4) and (5) enables us to show that the same distributors offer more complex products in countries in which ETFs have, than in countries in which they have not, entered the market.

We implement two additional analyses to mitigate concerns regarding the potentially endogenous nature of ETF entry in a given country. First, we re-run our difference-in-differences methodology, including interaction terms between being treated and a dummy equal to one for the year preceding the ETF entries in column (2). The initial interaction term remains statistically significant, but this additional term is not, indicating the absence of a pre-existing increasing trend of complexity prior to the entry of ETFs. A hazard model for ETF entry on level of complexity, the results of which are reported in the online appendix, also supports the absence of correlation.

These quantitative results are consistent with qualitative discussions with practitioners that suggest that ETF entries are driven mainly by institutional details at the country level, ETF eligibility for tax-efficient schemes being one of the main drivers.

4 Interpretation: Motives for Financial Complexity

In this section, we consider potential motives for financial complexity in light of the stylized facts elaborated above. Our results are hard to reconcile with a *completing markets* view, being more consistent with banks catering to yield seeking investors, confounding unsophisticated investors, and exploiting financial complexity to mitigate competitive pressure.

4.1 Completing Markets

A. Risk Sharing

If financial innovation's traditional aim of improving risk sharing (Allen and Gale (1994)) holds, banks' complex retail structured product offerings are meant to complete markets for retail investors. This motive is supported by the fact that many retail structured products allow retail investors to sell options. In practice, indeed, it is difficult for retail investors to directly write options, as to do so requires managing a margin account, and European regulators typically ban these types of transactions. However, that structured products make option sales possible not via simple, transparent instruments, but only through increasingly complex transactions, is difficult to explain in terms of demand for options.

The retail market for structured products may also offer a channel through which banks can transfer specific risks to retail investors. Although this hypothesis is difficult to test empirically owing to data limitations, discussions with practitioners suggest that banks do, indeed, offload certain stock market exposures through retail structured products. The correlation of household income with the stock market being relatively low, at least in the short term, this might constitute a welfare improving way to share some financial system risk. That a large share of retail structured products are bought through savings banks by relatively low-income households that might not be able to absorb liquidity shocks in the negative state of nature, however, calls into question the adequacy of this form of risk sharing.

Among other stylized facts described in the previous section that are hard to reconcile with the *completing markets* motive for the retail market for structured products is that the most complex products are offered by savings banks, the clients of which tend to be neither affluent nor investment savvy. It is thus unlikely that these households possess either the sophistication required to comprehend these products or the diversified portfolios that they might complement.

We also observe that the share of products exposed to stock market downside risk increased during the financial crisis. Under the reasonable assumption that retail investors are more risk averse than financial institutions, we should observe the opposite, the more so as risk aversion increased following the financial crisis (Guiso et al. (2013)).

Lastly, if markets are efficient and complex products better match retail investor demand, the innovations we observe should have been quickly disseminated, not progressively implemented. Indeed, the so-called innovations of the retail market for structured products are minor, and already existed in other markets. That the simplest products have progressively been removed from the market is also hard to reconcile with the intention of offering a full range of products that perfectly fits demand.

B. Gambling by Retail Investors

Neither does our analysis support the hypothesis that complex retail structured products afford gambling opportunities that motivate individuals' investment decisions (Kumar (2009)).

Many of the products in our sample present the opposite of a lottery payoff; as they are implicitly selling options, they provide a small gain with high probability and large loss with small probability. Our analysis excludes the product type most amenable to gambling motives, pure option products, and turbos and warrants, although they present lottery-like payoffs (low probability of a very high gain), appeal to a small investor base not representative of the retail structured product market as a whole. Yet another fact that is difficult to reconcile with the gambling hypothesis is that some households invest a significant fraction of their financial wealth in these products, as through life insurance products.[32] Finally, although they have met with little success, the fact of numerous households suing UK, French, German, Swiss, and Spanish banks for poor product performance argues against

[32]In Europe, life insurance contracts are hugely popular, constituting more than 26% of household financial wealth. Source: Household Finance and Consumption Survey, available at www.ecb.europa.eu.

the hypothesis that the retail structured product market essentially targets households that want to gamble.[33]

4.2 Catering to Yield Seeking Retail Investors

Retail investors seeking high yield products in a low interest rate environment is another possible explanation for the increase in financial complexity. Salience theory holds that investors tend to overweight some product attributes and neglect others, depending on the investment environment (Bordalo et al. (2012), Bordalo et al. (2013)). Investors might thus focus on, and consider quasi-certain, the salient coupon of a structured product even if the coupon remains conditioned on certain complex contingencies. The product complexity engenders uncertainty with respect to both the set of payoffs eventually received and corresponding probabilities.

During periods of low interest rates, headline rates become particularly salient to retail investors (Di Maggio and Kacperczyk (2014)). This can lead to the well-documented "reaching for yield" phenomenon (Rajan (2011), Yellen (2011), Becker and Ivashina (2014)).[34]

Two of our results are consistent with the hypothesis that banks use complexity to support a high headline rate. As previously shown, the level of the headline rate is positively correlated with product complexity, with a large economic significance. We further find that the higher a distributor's funding cost, the lower the financial complexity of the products it offers. High funding costs can support relatively simple products with an attractive headline rate because the offering banks use the products as funding tools. Banks that cannot offer simple products at an attractive rate because of lower funding costs offset their local relative disadvantage by improving the headline rate through complexity.

[33]In September 2008, in Switzerland, for example, the Lehman Brothers default prompted a number of litigation cases around the failure of CHF700 million of "capital guaranteed" products.

[34]This phenomenon can be reinforced by misrepresentation, as when banks intentionally misrepresent product final payoffs to improve investor expectations (Griffin and Maturana (2014)).

4.3 Confusing Retail Investors

Banks may use complexity to intentionally confuse, and extract rents from, investors. There are two main channels for employing obfuscation to extract rents from consumers. One is to increase search costs, which leads to oligopoly (e.g., Salop and Stiglitz (1977), Varian (1980); Stahl (1989)), or even monopoly (Diamond (1971)), pricing. The other is to price discriminate between sophisticated and unsophisticated consumers, as by adding expensive facultative "add-ons" or "shrouded attributes" to a base good (Ellison (2005) and Gabaix and Laibson (2006)). Our stylized facts are remarkably consistent with the empirical implications of these models of consumer obfuscation.

First, the markups embedded in retail structured products are large and an increasing function of product complexity. Second, complex products have lower *ex post* performance, and average *ex post* performance is lower than the risk free rate. In line with these stylized facts, Ellison (2005) and Gabaix and Laibson (2006)'s models of consumer obfuscation predict that more complex products are more profitable for the distributing firms.

Second, product complexity has increased over the years, enlarging the potential gap between what can be comprehended by households that remain financially unsophisticated (Lusardi et al. (2013)) and the knowledge and cognitive burden imposed by these products. This stylized fact is also consistent with banks intentionally inducing confusion by resetting households' possible learning (Carlin and Manso (2011)).

Third, savings banks offer relatively more complex products to clients whose low savings capacity limits their financial sophistication. This stylized fact supports the theoretical predictions of Gabaix and Laibson (2006) and Ellison (2005), who show the offer of more complex products to be intended to extract rent from unsophisticated households.[35]

Taken together, these results strongly suggest banks' use of complexity to maintain market opacity and extract a rent from investors unaware of their lack of sophistication.

[35] An important distinction of the "shrouded equilibrium" obtained in Gabaix and Laibson (2006) is that within the retail market for structured products there is no cross-subsidy between sophisticated and unsophisticated investors through a loss-leader base product.

4.4 Mitigating Competition between Banks

A complementary motive for financial complexity is to mitigate competitive pressure. This hypothesis is more explicative of the relative level of complexity across banks and time than of its absolute level.

Whereas competition should, in a frictionless market, drive product markups close to zero, independent of the level of complexity, we observe product markup to be an increasing function of product complexity. This result is consistent with the predictions of models of product differentiation: firms innovate, and thereby increase complexity, to offset competition and preserve their margin.

We further observe a positive correlation between product differentiation (measured in terms of the number of product types offered), and competitors, at the country level. Even competitors with similar client bases appear to specialize in different products.

Finally, the entry of ETFs, a simpler, low cost substitute for retail structured products, leads to an increase in the level of financial complexity. To rationalize this empirical fact, we derive from Carlin (2009) a simple model that predicts the entry of a new competitor to increase competition for sophisticated investors. Intensified competition in the sophisticated segment of the market increases the incentives for incumbent banks to sell complex products to capture the unsophisticated segment of the market. The model is presented in the online appendix.

4.5 Limits of Complexity

We also consider potential costs of complexity to issuers that can limit the effects of the foregoing motives. These include marketing, reputation, and litigation costs as well as hedging costs at the structuring level. Marketing costs for these products, because they might require longer explanations, might initially be higher than for mutual funds. We know, however, from practitioners' documentation, that the sales "pitch" largely focuses on the most salient features, which significantly simplifies the selling process. Additionally, investors' buy and hold strategy and the absence of performance reporting prior to product maturity ensure that "maintenance" advice is minimal relative to mutual funds. These products thus appear unlikely to be more labor intensive than mutual funds.

Litigation and reputation risks may exert downward pressure on innovator creativity and consequent complexity. However, investors who generally follow a buy and hold strategy typically become aware of a potential loss only at the end of a product's maturity. This market characteristic, coupled with the legal expertise that shields banks against accusations of mis-selling, limits, or at least delays, litigation and reputation costs. Although several groups of investors have sued banks over these products, few or none have been awarded financial compensation.

These additional costs, being by nature difficult to measure, are unlikely sufficient to fully absorb the earlier documented large difference in markup.

The cost of complexity raises, more generally, the question of the equilibrium level of complexity. In addition to previously discussed costs, the threat of investors who become aware of their unsophistication exiting the market may exert downward pressure on the level of complexity. This latter implicit cost of complexity is likely to be the main explanation for why complexity increases gradually.

5 Conclusion

Studying financial complexity is key to understanding modern financial markets. We use unique data on a large market of investment products marketed to households, specifically, retail structured products, to explore the motives for complex financial products.

A measure of financial complexity developed by performing a text analysis of the term sheets of 55,000 retail structured products issued in 17 European countries since 2002 shows financial complexity to have significantly increased over time. We further observe exposure to the downside risk embedded in these structured products to have increased during our sample period.

We also investigate the relationship between financial complexity and product returns.

Calculating the fair value of a subsample of products shows relatively more complex products to have higher markups. Consistent with this result, financial complexity predicts lower *ex post* performance for products in our sample that have matured. Conversely, the headline rate is positively correlated with a product's complexity.

Analyzing financial complexity at the distributor level, we find distributors that target low-income investors (e.g., savings banks) to offer relatively more complex products. Additionally, because they can therefore offer high paying deposits, banks with high funding costs can offer less complex products than banks with lower funding costs.

At the country level, our results suggest that competition amplifies rather than mitigates migration towards greater complexity. Indeed, average complexity increases when a simple substitute product enters the market or the number of competitors increases.

These stylized facts are difficult to reconcile with the view that retail structured products are offered to complete the market for households. The design of retail structured products is more consistent with banks catering to households seeking high yield in a low interest environment and with an obfuscation motive for financial complexity. Our findings raise questions about regulation and investor protection in retail finance. Adequately regulating financial complexity represents one of the greatest challenges of modern financial markets (Schwarcz (2009)).

References

Allen, F. and Gale, D. (1994). *Financial Innovation and Risk Sharing*. MIT press.

Amromin, G., Huang, J. C., Sialm, C., and Zhong, E. (2013). Complex Mortgages. *Working Paper*.

Anagol, S., Cole, S., and Sarkar, S. (2013). Understanding the Advice of Commissions-Motivated Agents: Evidence from the Indian Life Insurance Market. *Harvard Business School Working Paper No. 12-055*.

Arnold, M., Schuette, D. R., and Wagner, A. (2014). Pay Attention or Pay Extra: Evidence on the Compensation of Investors for the Implicit Credit Risk of Structured Products. *Working Paper*.

Becker, B. and Ivashina, V. (forthcoming, 2014). Reaching for Yield in the Bond Market. *Journal of Finance*.

Bergstresser, D. and Beshears, J. (2010). Who Selected Adjustable-Rate Mortgages? Evidence from the 1989-2007 Surveys of Consumer Finances. *Harvard Business School Working Paper No. 10-083*.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2012). Salience Theory of Choice under Risk. *Quarterly Journal of Economics*, 127(3):1243–1285.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2013). Competition for Attention. *NBER Working Paper No. 19076*.

Bucks, B. and Pence, K. (2008). Do Borrowers Know Their Mortgage Terms? *Journal of Urban Economics*, 64(2):218–233.

Caballero, R. J. and Simsek, A. (2009). Complexity and Financial Panics. *NBER Working Paper No 14997*.

Carlin, B. I. (2009). Strategic Price Complexity in Retail Financial Markets. *Journal of Financial Economics*, 91(3):278–287.

Carlin, B. I., Kogan, S., and Lowery, R. (2013). Trading Complex Assets. *Journal of Finance*, 68(5):1937–1960.

Carlin, B. I. and Manso, G. (2011). Obfuscation, Learning, and the Evolution of Investor Sophistication. *Review of Financial Studies*, 24(3):755–785.

Di Maggio, M. and Kacperczyk, M. (2014). The Unintended Consequences of the Zero Lower Bound Policy. *Working Paper*.

Diamond, P. A. (1971). A Model of Price Adjustment. *Journal of Economic Theory*, 3:156–168.

Dumas, B., Fleming, J., and Whaley, R. E. (1998). Implied Volatility Functions: Empirical Tests. *Journal of Finance*, 53(6):2059–2106.

Ellison, G. (2005). A Model of Add-On Pricing. *Quarterly Journal of Economics*, 120(2):585–637.

Gabaix, X. and Laibson, D. (2006). Shrouded Attributes, Consumer Myopia, and Information Suppression in Competitive Markets. *The Quarterly Journal of Economics*, 121(2):505–540.

Ghent, A., Torous, W., and Valkanov, R. (2014). Complexity in Structured Finance: Financial Wizardry or Smoke and Mirrors? *Working Paper*.

Griffin, J. M., Lowery, R., and Saretto, A. (2014). Complex Securities and Underwriter Reputation: Do Reputable Underwriters Produce Better Securities? *Review of Financial Studies*, 27(10):2872–2929.

Griffin, J. M. and Maturana, G. (forthcoming, 2014). Who Facilitated Misreporting in Securitized Loans? *Journal of Finance*.

Grinblatt, M. and Titman, S. (1994). A Study of Monthly Mutual Funds Returns and Performance Evaluation Techniques. *Journal of Financial and Quantitative Analysis*, 29(3):419–444.

Guiso, L., Sapienza, P., and Zingales, L. (2013). Time Varying Risk Aversion. Technical Report 19284.

Hackethal, A., Haliassos, M., and Jappelli, T. (2012). Financial Advisors: A Case of Babysitters? *Journal of Banking & Finance*, 36(2):509–524.

Henderson, B. J. and Pearson, N. D. (2011). The dark side of financial innovation: A case study of the pricing of a retail financial product. *Journal of Financial Economics*, 100(2):227–247.

Hens, T. and Rieger, M. O. (2014). Can Utility Optimization Explain the Demand for Structured Investment Products? *Quantitative Finance*, 14(4):673–681.

Jensen, M. (1968). The Performance of Mutual Funds in the Period 1945-1964. *Journal of Finance*, 23(2):389–416.

Jorgensen, P., Norholm, H., and Skovmand, D. (2011). Overpricing and Hidden Costs of Structured Bonds for Retail Investors: Evidence from the Danish Market for Principal Protected Notes. *Working Paper*.

Karabulut, Y. (2013). Financial Advice: An Improvement for Worse? *Working Paper*.

Kumar, A. (2009). Who Gambles in the Stock Market? *Journal of Finance*, 64(4):1889–1933.

Longstaff, F. A. and Schwartz, E. S. (2001). Valuing American Options by Simulation: A Simple Least Square Approach. *Review of Financial Studies*, 14(1):113–147.

Lusardi, A., Mitchell, O. S., and Curto, V. (2010). Financial Literacy among the Young. *Journal of Consumer Affairs*, 44(2):358–380.

Lusardi, A., Mitchell, O. S., and Curto, V. (2013). Financial Literacy and Financial Sophistication Among Older Americans. *Journal of Pension Economics and Finance*, February:1–20.

Lusardi, A. and Tufano, P. (2009). Debt Literacy, Financial Experiences and Overindebtedness. *NBER Working Paper*, (14808).

Rajan, R. G. (2011). *Fault Lines: How Hidden Fractures Still Threaten the World Economy*. Princeton University Press.

Salop, S. and Stiglitz, J. (1977). Bargains and Ripoffs: A Model of Monopolistically Competitive Price Dispersion. *Review of Economic Studies*, 44(3):493–510.

Sato, Y. (2014). Opacity in Financial Markets. *Review of Financial Studies*, (Forthcoming).

Schwarcz, S. (2009). Regulating Complexity in Financial Markets. *Washington University Law Review*, 87(2):211.

Stahl, D. O. (1989). Oligopolistic Pricing with Sequential Consumer Search. *The American Economic Review*, 72(4):700–712.

Sun, Y. (2014). Investor Selection and the Asymmetric Effects of Index Fund and ETF Innovations. *Working Paper*.

Varian, H. R. (1980). A model of sales. *The American Economic Review*, 70(4):651–659.

Yellen, J. (2011). Remarks at the International Conference: Real and Financial Linkage and Monetary Policy. *Bank of Japan*.

A Figures

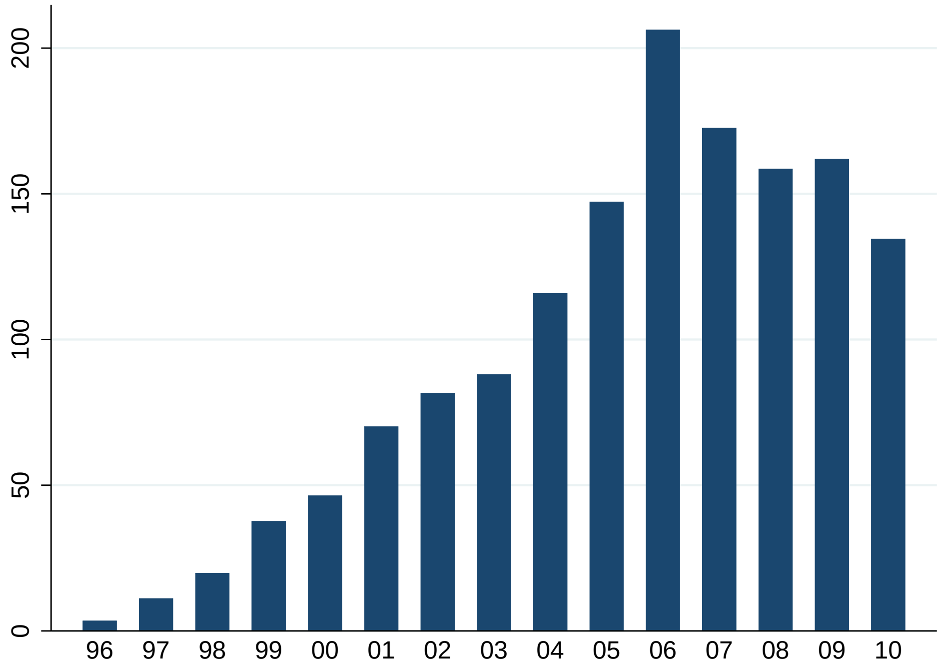

FIGURE I. Volume Sold per Year, in billion euros

This figure shows, in billions of euros, volume issuance of tranche retail structured products in the European market over the 1996-2011 period. The countries include Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Hungary, Ireland, Italy, Netherlands, Norway, Poland, Portugal, Spain, Sweden, and the United Kingdom.

Dimension	**Features**
Primary Feature	Call Put Spread Pure Income Digital Floater Others
Initial Subsidy	Discount Guaranteed Rate Bonus
Downside Modulation	Best of Option Worst of Option Himalaya Kilimanjaro Rainbow Reverse Convertible Precipice
Upside Modulation	Cap Fixed Upside Flip Flop
Path Dependence	Cliquet Asian Option Parisian Option Averaging Delay Catch-up Lookback
Exotic Condition	American Option Range Target Moving Strike Bunch Podium Annapurna
Early Redemption	Knockout Callable Puttable

FIGURE II. Typology of Retail Structured Product Features

This figure details the possible dimensions of a retail structured product and corresponding features. The features of each dimension are mutually exclusive. Each structured product possesses one primary feature. Other dimensions are facultative. The features are described in the Appendix.

	Example 1: Unigarant: Euro Stoxx 50 2007	Example 2: Vivango Actions Mars 2017
Details		
Year	2002	2010
Country	Germany	France
Provider	Volksbanken Raiffeisenbanken	La Banque Postale
Description	This is a growth product linked to the performance of the DJ Euro Stoxx 50. The product offers [*100% capital guarantee at maturity*]$^{(1)}$ along with a [*predetermined participation of 50% in the rise of the underlying*]$^{(1)}$ over the investment period	This is a growth product linked to a basket of 18 stocks of companies selected as being the largest companies by market capitalization from the Euro Stoxx 50 at the time the product was launched. Every year, the average performances of [*the three best-performing shares*]$^{(2)}$ in the basket are recorded compared with their initial levels. These three shares [*are then removed*]$^{(2)}$ from the basket. At maturity, the product offers [*a minimum capital return of 100%, plus 70% of the average of these performances*]$^{(1)}$ [*recorded annually throughout the investment period*]$^{(3)}$.
Payoff Features	Call	Call - Himalaya - Asian Option
Complexity Measures		
# Features	1	3
# Scenarios	1	1
Length	226	537
Promised return	50%	70%

[...]$^{(x)}$: Text identifying Payoff x

FIGURE III. Measuring Complexity

This figure shows how two actual product descriptions are converted to quantitative measures of complexity.

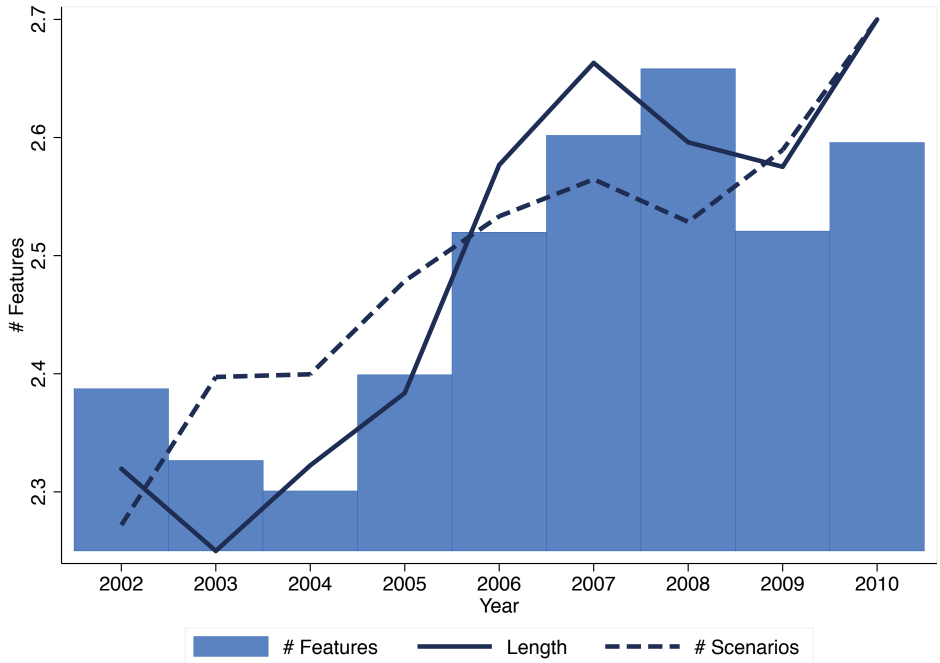

FIGURE IV. Predicted Product Complexity by Year

This figure shows the predicted complexity of retail structured products by year, calculated by estimating an OLS regression of product complexity over year fixed effects, controlling for product and distributor characteristics. The sample covers 55,585 products from 17 European countries. Complexity is measured as the number of features embedded in each product payoff formula, length of the pay-off descriptive, and number of scenarios. We obtain these complexity measures through a text analysis of the detailed text description of the final payoff formula (from Euromoney SRP). The scale of the Y axis, provided for purposes of clarity, refers only to the number of features.

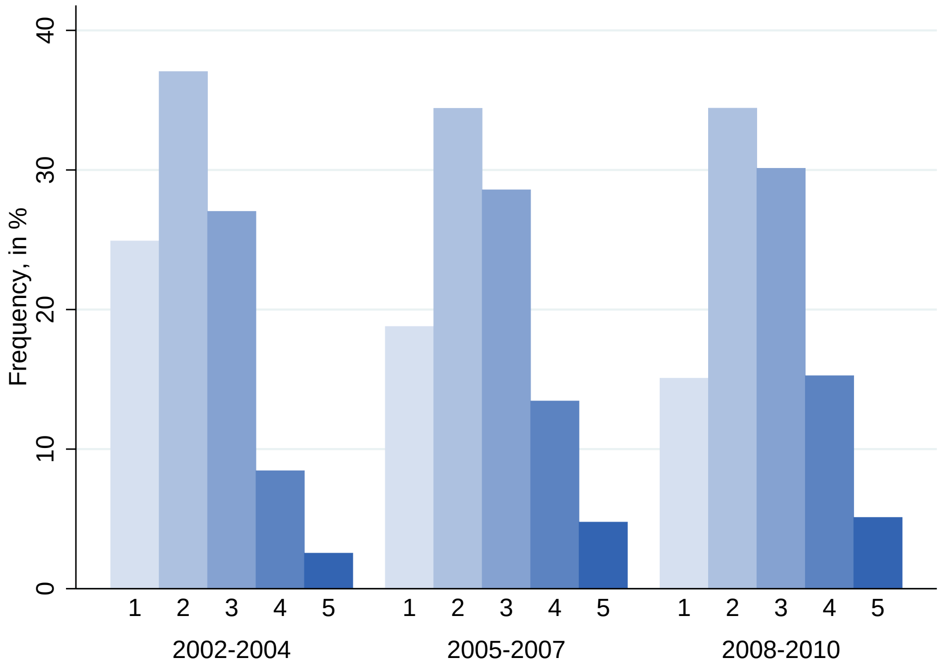

Figure V. Evolution of the Distribution of Product Complexity

This figure shows the evolution of the distribution of our complexity variable over three periods: 2002-2004, 2005-2007, and 2008-2010. The sample covers 55,585 products from 17 European countries. Complexity is measured as the number of features embedded in each product payoff formula. We obtain this complexity measure by means of a text analysis of the text description of the final payoff formula (source of the payoff formula: Euromoney SRP).

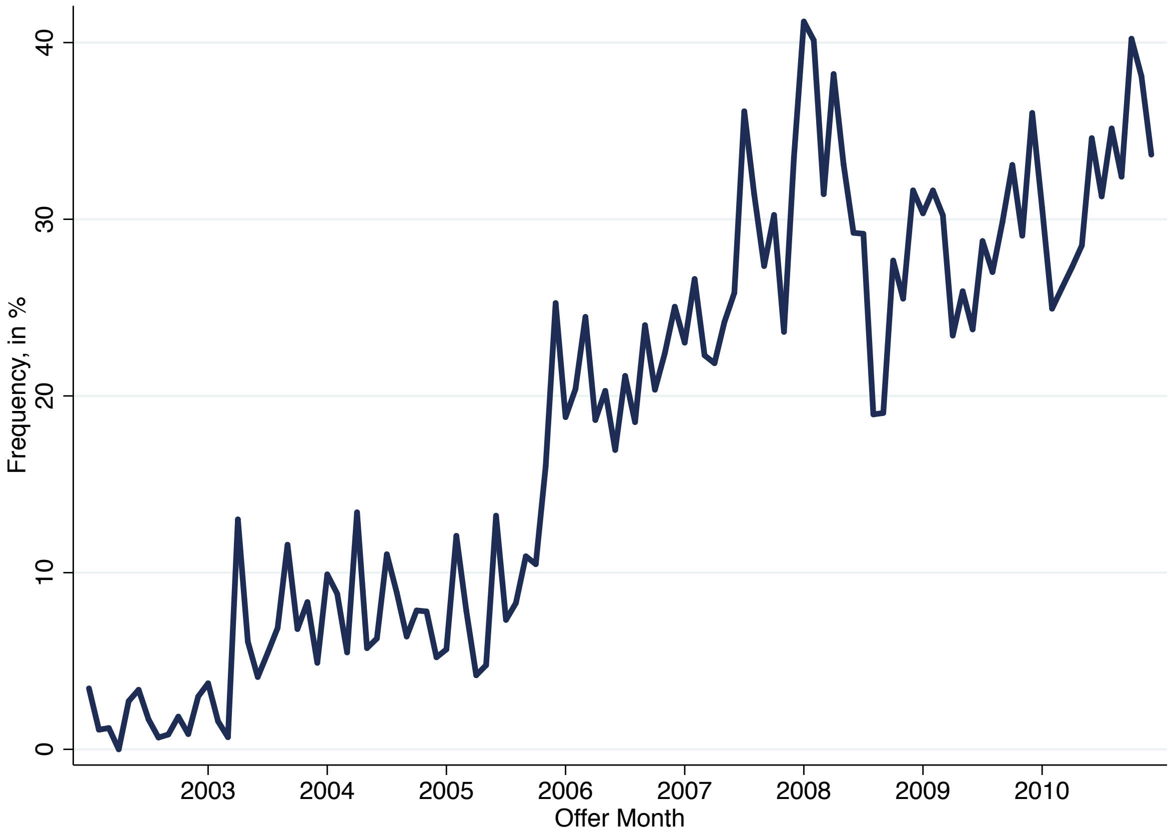

FIGURE VI. Ratio of Products Exposed to Downside Risk

This figure shows the share of products issued over the 2002-2010 period that include in their pay-off a reverse convertible feature at a monthly frequency. The reverse convertible feature is defined in the Appendix.

B Tables

Table I. Country-Level Summary Statistics

Country	**Total Issue Billion Euros** *2002-2010* **(1)**	**# Products** *2002-2010* **(2)**	**# Distributors** *2002-2010* **(3)**	**% of Fin. Savings** *2010* **(4)**	**% of Mutual Funds** *2010* **(5)**
Italy	343	5,724	79	2.8	28
Spain	204	4,734	60	2.8	37
Germany	162	14,861	43	2.3	22
France	158	1,801	73	2	12
Belgium	135	4,021	46	8.5	69
United Kingdom	110	6,135	141	1.1	8.3
Netherlands	37	2,741	36	1.1	30
Sweden	34	4,529	31	2	9
Portugal	24	928	24	3.2	73
Austria	20	3,275	42	3.3	28
Denmark	17	563	31	.82	7.2
Ireland	16	1,075	40	2.1	.91
Norway	15	1,288	25	.28	1.6
Finland	9	1,251	25	2.1	9.3
Poland	8	1,518	45	1.5	19
Czech Republic	6	939	24	2.8	45
Hungary	2	202	15	1.9	22
European Market	*1,300*	*55,585*	-	*3*	*12.9*

This table reports the aggregated volume of retail structured product issuance (column (1)), total number of products sold since inception (column (2)), and number of distributors in each national market (column (3)). Column (4) shows the penetration rate of retail structured products, defined as the share of household financial savings, and column (5) compares assets under management for the retail structured products and mutual fund industries. Retail structured products can take the form of a structured note, which is not included in the mutual fund industry. The figures reported in the table are only for tranche products, non-standardized structured products with a limited offer period and maturity date that account for 90% of market volume. Flow (e.g., bonus and discount certificates) and leverage (e.g. warrants and turbos) products (which, although together account for more than 1 million issues since 2002), represent only 10% of market volume. Data source is Euromoney Structured Retail Products.

Table II. Product and Distributor Summary Statistics

	2002-2004 (1)	2005-2007 (2)	2008-2010 (3)	Full Sample (4)
Underlying Type (in %)				
Equity	75.6	72.7	66.0	70.1
Interest Rate	6.4	7.1	21.5	12.5
Commodity	0.5	3.1	3.02	2.6
FX Rate	1.8	4.1	1.8	2.8
Other	15.9	12.9	7.7	11.4
Distributor Type, Number (Market Share, in%)				
Commercial Banks	100 *(68.9)*	133 *(63.2)*	133 *(64.1)*	164 *(65.4)*
Saving Banks	19 *(12)*	19 *(16)*	23 *(21)*	26 *(16.4)*
Private Banks	95 *(14.5)*	115 *(15)*	148 *(13.2)*	201 *(14.4)*
Insurance	24 *(2.4)*	35 *(3.4)*	32 *(1.2)*	44 *(2.4)*
Other	11 *(2.2)*	18 *(1.6)*	16 *(0.3)*	28 *(1.4)*
Total	249	320	352	463
Product Format (in %)				
Collateralised Asset	56.9	37.7	26.4	36.9
Non-Collateralised Asset	43.1	62.3	73.6	63.1
Volume (in million euros)				
Mean	38.7	22.3	16.1	20.9
10th percentile	5.9	3.5	2.1	3.1
90th percentile	84.0	41.4	25.0	38.2
Product Design				
Capital Guarantee (in %)	91.3	78.7	74.0	79.2
Average Maturity (in years)	5.1	4.7	4.6	4.7

This table reports summary statistics for characteristics of retail structured products including underlying asset, distributor type, format, volume, and design. The sample covers 55,585 products from the 17 European countries listed in Table 1. The data source is Euromoney SRP.

Table III. Product Complexity and Markup

	Product Yearly Markup, in %					
	(1)	**(2)**	**(3)**	**(4)**	**Disclosed Fees Incl. (5)**	**PDE Pricing (6)**
Summary Statistics						
Mean	3.51				6.29	2.86
Median	3.06				4.95	2.47
Standard Deviation	4.49				6.22	4.58
OLS Estimation						
# Features	0.342***	0.296***	0.295***	0.299**	0.349**	0.394**
	(0.101)	(0.107)	(0.108)	(0.148)	(0.136)	(0.178)
Credit Risk Dummy	-0.339	-0.080	-0.121	-0.385	-1.655***	-0.355
	(0.265)	(0.372)	(0.437)	(0.300)	(0.446)	(0.439)
Controls						
Distributor FE	-	Yes	-	-	-	-
Primary Feature FE	-	-	Yes	-	-	-
Facultative Feature FE (Main)	-	-	-	Yes	-	-
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	141	141	141	141	141	103
R^2	0.211	0.818	0.818	0.279	0.303	0.159

The upper half of the table displays summary statistics for the yearly markup, in percent, of product notional for all products indexed to the Euro Stoxx 50 sold in Europe in July 2009 (101 products) as well as a random sample of 47 products indexed to the Euro Stoxx 50 in October 2010. The bottom half of the table displays the coefficients of OLS regressions in which the dependent variable is the yearly markup and the explanatory variables our three complexity measures. Markups are computed as the difference between the offer price and the product's calculated fair value, obtained using the Longstaff and Schwartz OLS Monte Carlo pricing methodology (Longstaff and Schwartz (2001)) with local volatility diffusion. Volatility surface data is from Eurex. The explanatory variable is the number of payoff features. Control variables include country and distributor fixed effects in addition to primary and added feature fixed effects. Standard errors are clustered at the distributor level (30 clusters) and reported in brackets. *, **, and *** represent statistical significance at the 10%, 5%, and 1% confidence levels, respectively.

Table IV. Product Complexity and Ex-post Performance

	Product Yearly Return, in %		
	(1)	(2)	(3)
Summary Statistics			
Mean	2.44		
Median	1.98		
Standard Deviation	6.21		
5Y Swap Rate	*3.77*		
OLS Estimation			
# Features	-0.361**		
	(0.159)		
# Scenarios		-0.420***	
		(0.140)	
Description Length			-0.002***
			(0.001)
Controls			
Capital Protection Dummy	Yes	Yes	Yes
Credit Risk Dummy	Yes	Yes	Yes
Underlying FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	7,359	7,359	7,359
R^2	0.417	0.418	0.417

The upper half of the table displays summary statistics for the yearly rate of return of participation products that matured before 2010 and average 5-year swap rate over the same period. The bottom half of the table displays the coefficients of OLS regressions in which the dependent variable is the yearly rate of return. The explanatory variables are our complexity measures: number of payoff features (column (1)), number of scenarios (column (2)), and length of the payoff description (column (3)). Control variables include country, year, distributor, underlying asset, and capital protection fixed effects, and a credit risk dummy for products that are non-collateralized. Standard errors are clustered at the distributor level and reported in brackets. Performance data is from Euromoney SRP. *, **, and *** represent statistical significance at the 10%, 5%, and 1% confidence levels, respectively.

Table V. Product Complexity and Headline Rate

	Headline Rate, in %							
	Coupon Products				**Participation Products**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
# Features	1.518**	1.527**			2.566***	2.294***		
	(0.669)	(0.645)			(0.538)	(0.576)		
# Scenarios			0.836**				3.668***	
			(0.401)				(0.501)	
Length				0.010***				0.010***
				(0.002)				(0.004)
Controls								
Distributor FE	-	Yes	-	-	-	Yes	-	-
Underlying FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Format FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maturity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Volume	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,590	12,590	12,590	12,590	18,664	18,664	18,664	18,664
R^2	0.225	0.326	0.220	0.229	0.083	0.173	0.091	0.081

This table displays the coefficients of OLS regressions in which the dependent variable is *Headline Rate*. The explanatory variables are our complexity measures, as defined previously. Regressions include the usual product and issuer characteristic controls. The sample is split into two panels: coupon products that pay a coupon at the end of each period, and participation products that offer a fixed participation in the performance of the underlying. *Headline Rate* is defined as the coupon offered in the best-case scenario for coupon products and, for participation products, as the highest level of participation in the performance of the underlying. Standard errors are clustered at the distributor level and reported in brackets. *, **, and *** represent statistical significance at the 10%, 5%, and 1% confidence levels, respectively.

Table VI. Complexity Measures and Financial Sophistication

	# Features	# Scenarios	Description Length
	(1)	(2)	(3)
Summary Statistics			
Savings Bank			
Mean	2.7	2.7	533
Standard Deviation	1.1	1.6	227
Max	8	16	2,595
Private Banking			
Mean	2.5	2.2	503.9
Standard Deviation	1.1	1.5	213
Max	7	9	2,102
Commercial Bank			
Mean	2.3	2.0	472.8
Standard Deviation	1.1	1.4	206
Max	7	11	2,203
Other			
Mean	2.5	2.2	503.9
Standard Deviation	1.1	1.5	213
Max	7	9	2,102
OLS Estimation			
Savings Bank	0.155**	0.514***	41.003**
	(0.074)	(0.119)	(18.501)
Private Bank	0.122**	0.062	12.004
	(0.049)	(0.075)	(8.733)
Controls			
Underlying FE	Yes	Yes	Yes
Format FE	Yes	Yes	Yes
Maturity	Yes	Yes	Yes
Volume	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	54,489	54,489	54,489
R^2	0.075	0.138	0.090

The upper half of the table displays summary statistics for our three measures of complexity by distributor type, the bottom half, OLS regressions in which the dependent variables are our three measures of complexity. The explanatory variables are dummy variables that indicate type of distributor. Number of payoff features is obtained through a text analysis of the detailed pay-off descriptive. Number of scenarios is constructed by counting the number of conditions in the product descriptive. Length is the number of characters of the payoff descriptive. Standard errors are clustered at the distributor-year level and reported in brackets. Data sources are Euromoney Structured Retail Products and Bankscope. *, **, and *** represent statistical significance at the 10%, 5%, and 1% confidence levels, respectively.

Table VII. CDS Spread and Product Complexity

	# **Features**	# **Scenarios**	**Length**
	(1)	**(2)**	**(3)**
Issuer's CDS spread	-0.016**	-0.024***	-4.618***
	(0.008)	(0.009)	(1.171)
Controls			
Distributor Type FE	Yes	Yes	Yes
Underlying FE	Yes	Yes	Yes
Format FE	Yes	Yes	Yes
Maturity	Yes	Yes	Yes
Volume	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Observations	11,838	11,838	11,838
R^2	0.187	0.358	0.270

This table displays coefficients of OLS regressions in which the dependent variable is product complexity. The explanatory variable is the level of the issuer's CDS spread, in %. CDS spreads are from Datastream, and cover the 2007-2010 period. Regressions include the usual product and issuer characteristic controls as well as quarter fixed effects. Standard errors are clustered at the distributor group quarter level and reported in brackets. *, **, and *** represent statistical significance at the 10%, 5%, and 1% confidence levels, respectively.

Table VIII. Competition, Complexity and Product Differentiation

	# Features		# Product Types
	Country Level	Distributor Level	Country Level
	(1)	(2)	(3)
# Competitors (per country)	0.016**	0.006*	2.203***
	(0.006)	(0.004)	(0.594)
Controls			
Distributor FE	-	Yes	-
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	132	2,865	144
R^2	0.661	0.425	0.815

This table displays the coefficients of OLS regressions on unbalanced panel data at the country and distributor level over the 2002-2010 period. All countries are included save Norway and Poland over the 2008-2010 period due to insufficient volume. The dependent variable is the average complexity of products at the country x year level for column (1), average complexity at the distributor level for column (2), and number of types of product offered at the country x year level for column (3). The explanatory variable for all columns is the number of competitors in the retail market for structured products at the country x year level. Standard errors, reported in brackets, are robust to heteroskedasticity in columns (1) to (3), and clustered at the distributor level in column (2). *, **, and *** represent statistical significance at the 10%, 5%, and 1% confidence levels, respectively.

Table IX. The Impact of ETF Introduction on Complexity

	# Features				
	Country Level			Distributor Level	
	(1)	(2)	(3)	(4)	(5)
ETF awareness × Post	0.260***			0.155**	
	(0.098)			(0.069)	
# ETFs			0.001**		0.001***
			(0.000)		(0.000)
ETF awareness × Y $= t-1$		-0.009			
		(0.114)			
ETF awareness × Y $= t$		0.214*			
		(0.125)			
ETF awareness × Y $> t$		0.407**			
		(0.165)			
Controls					
Distributor FE	-	-	-	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	112	112	135	2,612	2,992
R^2	0.698	0.707	0.610	0.443	0.434

This table displays the coefficients of OLS regressions on unbalanced panel data at the country and distributor level over the 2002-2010 period. All countries are included except Hungary. The dependent variable is the average complexity of products for a given country (Columns (1) to (3)), and for a given distributor in a given country (Columns (4) and (5)), for a given year. The difference-in-differences methodology is based on the staggered entries of ETFs across European countries. $ETFAwareness \times Post$ is a dummy that is equal to one if investors have become aware of the ETF asset class, as measured at the country level by the appearance of the search-term "ETF" in Google Trend. *Number of ETFs* represents the number of ETFs listed in each country for each year, per Morningstar Direct Data. Standard errors are clustered at the distributor level and reported in brackets. *, **, and *** represent statistical significance at the 10%, 5%, and 1% confidence levels, respectively.

A - Retail Structured Product Typology

Feature Name	Definition
Dimension 1: Primary Feature	
Altiplano	The product offers a capital return of 100% plus a series of fixed coupons on each subperiod if the underlying is above a predefined barrier.
Floater	The product offers a capital return of 100% plus a series of coupons that rise when the underlying reference rate rises.
Pure Income	The product offers a capital return of 100% plus a series of fixed coupons.
Digital	The product offers a capital return of 100% plus a fixed coupon paid at maturity if the underlying is above a predefined barrier.
Call	The product offers a capital return of 100% plus a fixed participation in the rise of the underlying.
Put	The product offers a capital return of 100% plus a fixed participation in the absolute value of the fall of the underlying.
Spread	The product offers a capital return of 100% plus a participation related to the spread between the performances of different underlyings (shares, rates, etc.).
Bull Bear	The final return is based on a percentage of the absolute performance of the underlying at maturity.
Dimension 2: Initial Subsidy	
Discount	The product offers a discount on the purchase of a given underlying, typically a stock or an index
Guaranteed Rate Bonus	The product offers an unconditional coupon for a given number of periods.
Dimension 3: Underlying Selection	
Best of Option	The return is based on the performance of the best performing underlying assets.
Worst of Option	The return is based on the participation in the performance of the worst performing underlying assets.
Himalaya	A pre-selected number of best-performing assets are permanently removed from the basket, or frozen at their performance level, at the end of each period until the end of the investment.
Kilimanjaro	The lowest and best performing assets are progressively eliminated, or ignored in subsequent calculations, during the investment period.
Rainbow	Best performing assets are weighted more heavily than those that do not perform as well.
Dimension 4: Exposure Modulation, Increased Downside	
Reverse Convertible	The product is capital guaranteed unless a performance criterion is not satisfied, in which case the capital return is reduced by the percentage fall in the underlying or the product pays back a predefined number of shares/bonds.
Precipice	The product is capital guaranteed unless a performance criterion is not satisfied.
Dimension 5: Exposure Modulation, Limited Upside	
Cap	The return is based on the participation in the performance of the worst performing underlying assets.
Fixed Upside	The best performances of a basket of stocks or set of subperiod returns are replaced by a predetermined fixed return.
Flip Flop	The coupons are fixed in the first periods and the distributor has the right to switch the investment into floating.

Dimension 6: Path Dependence

Cliquet	The final return is determined by the sum of returns over some pre-set periods.
Asian Option	The final return is determined by the average underlying returns over some pre-set periods.
Parisian Option	The value of the return depends on the number of days in the period in which the conditions are satisfied.
Averaging	The final index level is calculated as the average of the last readings over a given period (more than one month).
Delay	Coupons are rolled up and paid only at maturity.
Catch-up	If a coupon is not attributed in a given period because the condition required for the payment is not met, that missed coupon and any subsequently missed coupon will be rolled up and attributed in the next period in which the condition is met.
Lookback	The initial/final index level is replaced by the lowest/highest level over the period.

Dimension 7: Exotic Condition

American Option	The conditions must be satisfied over the entire period considered.
Range	The performance of the underlying is within a range.
Target	The sum of the coupon reaches a predefined level.
Moving Strike	The conditional levels are moving.
Bunch	The top barrier/cap concerns each asset, the bottom barrier the entire basket.
Podium	The underlying is a basket and the final returns depend on the number of shares that satisfy the conditions.
Annapurna	The condition must be satisfied for any security in the underlying basket.

Dimension 8: Early Redemption

Knockout	The product matures early if specific conditions are satisfied.
Callable	The issuer can terminate the product on any coupon date.
Puttable	The investor can terminate the product on any coupon date.

This table describes how a payoff formula is broken down into distinct features. Each family of facultative features contains features that are mutually exclusive. A structured product possesses exactly one main feature that defines the product's primary structure.

B - List of Variables

Number of Features: Our main measure of complexity (see section 2.2 for a detailed description).

Number of Scenarios: The number of different scenarios that affect the payoff formula, as measured by the occurrence of such conditional subordinating conjunctions as “if,” “when,” and “whether” in the text description of the payoff formula.

Length: The number of characters in the textual description of the payoff formula.

Average Complexity: The yearly average of financial complexity, weighted by product issuance volume, calculated at the market, country, or distributor levels.

Issuance Volume: The total volume of products sold during the offer period.

Markup: The difference between the issuance price and fair value calculated using a local volatility diffusion model (see Section 2.3 for a detailed description of the pricing methodology).

Credit Risk: Indicator variable for non-collateralized products, which include structured notes and deposits and bear the credit risk of the issuer.

Capital Guaranteed: Indicator variable for products that offer at minimum the initially invested amount at maturity.

Headline Rate: The rate that results from a product’s primary feature, for coupon products, the coupon offered in the baseline scenario, and for participation products, the baseline level of participation in the positive performance of the underlying.

Participation Product: Indicator variable for products that offer a participation in the positive performance of the underlying.

Coupon Product: Indicator variable for products that pay a coupon at the end of each period or at maturity, depending on the performance of the underlying.

Savings Bank: Indicator variable for a product distributed by a savings bank.

Commercial Bank: Indicator variable for a product distributed by a commercial bank.

Private Bank: Indicator variable for a product distributed by a private bank.

CDS spread: The 5y senior CDS spread of the bank distributing the product, obtained from Datastream.

ETF awareness: Indicator variable for the term "ETF" being searched on Google for a given country; data source is Google Trend.

Number of ETFs: The number of ETFs listed in a given country; data source is Morningstar Direct Data.

Number of Competitors: The numbers of distributors having issued at least one product in a given country in a given year.

Number of Product Types: The number of distinct feature combinations marketed at least once in a given country in a given year.

Volatility Data : The implied volatility inferred from options mid quotes on the Eurex exchange.