# THE MOTIVES FOR FINANCIAL COMPLEXITY: AN EMPIRICAL INVESTIGATION *

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**Abstract**

This paper investigates why financial institutions issue complex securities. We focus on a large market of investment products targeted exclusively at households: retail structured products. We develop three measures of their complexity via a text analysis of the term sheets of all 55,000 retail structured products issued in Europe between 2002 and 2010. We find that the complexity of structured products has significantly increased over this period, as well as product differentiation. Building on the salience theory of choice, we then hypothesize that banks use complexity to cater to yield seeking investors, while increasing their own profits. We find three types of empirical evidence consistent with this view. First, we show that more complex products offer higher promised returns. Second, calculating the fair value of a subsample of products, we find that more complex products are more profitable for issuers, and that their *ex post* performance is lower. Finally, banks issue more complex products in environments in which promised returns are likely to be more salient.

*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 empirically a related motive for issuing complex products: catering to yield seeking investors.

We focus on a large category of investment products broadly marketed to households worldwide : retail 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 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 are consistent with financial institutions designing complex securities to appeal to yield seeking investors, and hence extract rents from them. The first step of our analysis is to develop a robust and replicable measure of product complexity, that we apply to 55,000 retail structured products.

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

At the market level, we document that the complexity of retail structured products has increased over time, with no discernable decrease during the financial crisis. We also show that the exposures embedded in these complex products have evolved over time, with an increasing share exposed to downside risk during the financial crisis. The level of product differentiation also increases significantly over our sample period.

To structure our micro-level empirical analysis, we borrow from the theoretical framework of saliency (Bordalo et al. (2012)). We write a simple model in which banks use complexity as a way to increase the promised return, but not the expected return, of financial securities. Investors appetite for the security is increased due to the saliency of this promised return, while banks can capture a larger profit as investors overweight the probability of positive outcome. We thus derive a series of empirical predictions that we empirically test in the retail market for structured products.

We first find that more complex products indeed offer a higher promised return than simpler products. Second, more complex products yield higher markups to the banks that distribute them. These *ex ante* higher markups translate into lower *ex post* performance for more complex products. Finally, we find that banks offer relatively more complex products in environments in which promised returns are more likely to be salient - i.e. when their funding costs are low. We also obtain two additional results that are broadly consistent with a salience theory of choice : entities that target investors with low financial sophistication, which are also more likely to be more salient thinkers, offer more complex products than institutions that target wealthier investors. Moreover, increased competition amplifies rather than mitigates evolution towards increasing financial complexity, which is consistent with bank competing on promised returns, and not on expected returns. All these results are consistent with the predictions from our theoretical framework.

The development of three robust and replicable measures of financial complexity is an important contribution of the present paper. Our main measure aims to capture the multi-dimensionality 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 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]

Our work contributes to several strands of the literature. First, our paper builds on the salience theory of investment (Bordalo et al. (2012), Bordalo et al. (2013)), and the literature documenting the reaching for yield phenomenon (Rajan (2011), Yellen (2011), Becker and Ivashina (2014)). Our work also directly relates to 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.

More generally, our work contributes to the growing literature on complex securities

[2] European regulation does not limit access to accredited investors, as is the case in the United States.
[3] http://www.structuredretailproducts.com/.

(Griffin et al. (2014), Ghent et al. (2014), Carlin et al. (2013), Amromin et al. (2013), Sato (2014)).

Our work also adds 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)).

Finally, 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.[4] 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.[5]

Our paper proceeds as follows. Our methodology for measuring the complexity of retail structured products is detailed in Section 2. In Section 3, we report market trends from our empirical investigation. In Section 4, we apply the saliency theoretical framework to our market. In Section 5, we test the empirical implications of this framework. We

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

[5] 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.

discuss potential alternative motives for issuing complex securities in Section 6. Section 7 concludes.

# 2 Measuring Financial Complexity

The retail market for structured products is an ideal laboratory to study financial product complexity. With assets under management close to one trillion dollars, the market is undeniably large. 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, explanations of the data used, and we describe the methodology we develop to measure complexity.

## 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.[6] 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.

> *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*

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

*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.[7] 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 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

[7]Source: Euromoney Structured Retail Products.

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

[8]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.

### *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).[9] 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.[10]

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.[11] 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).[12]

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 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.

[9]www.structuredretailproducts.com.

[10]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).

[11]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.

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

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

One of the main contribution of the paper is to develop robust and replicable measures of financial complexity. Our main measure of pay-off complexity aims at capturing the multidimensionality of the contracts offered in retail structured products, the rationale being that the difficulty of understanding a product pay-off formula, and comparing it with the ones of other products increases with the number of dimensions.[13]

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 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

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

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.[14] 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.

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

# 3 Market Trends

Our measures of complexity allow us to explore market trends for retail structured products over our sample period.

### *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.[15]

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.

[15]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 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.

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

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.

### *C. Evolution of Market Differentiation*

Another striking evolution of the retail market for structured product is the increase in product differentiation. Figure VII plots the number of different types of products sold in a given year. We define a type of product as a different combination of pay-off features. The number of types of product is both large and increasing, with more than 500 different types of products marketed in a given year towards the end of the sample.

INSERT FIGURE VII

# 4 Complex Financial Products: Theoretical Framework

The next step of our investigation is to explain the cross-section of complexity at the product level. For this purpose, we apply the saliency framework from Bordalo et al. (2012) to the retail market for structured products, and develop empirical predictions on the level of complexity. The main rationale of applying this framework for the retail market of structured product is the following. While banks cannot add shrouded attributes to an investment product, as opposed to credit cards for instance, they can inflate investor expectations through the design of the security payoff.

## 4.1 Banks

We consider two banks, 1 and 2, which present the same level of risk of default.

Bank 1 offers a simple product, where the investor initially invests 1, and receives $1 + R$ at maturity with probability $p$, and 1 with probability $1 - p$. This product is typically a term deposit, where the investor gets a promised rate, unless the bank defaults.

Bank 2 offers a complex product with the same initial investment, but whose return is equal to $1 + \alpha R$, $\alpha > 1$, with a probability $p' = \frac{p}{\alpha}$, and is equal to 1 with probability $1 - p'$. This product is typically a non-collateralized retail structured product that offers a promised return conditional on the underlying index performance meeting one or several criteria, and zero otherwise. (See appendix for the term sheet of one of these products).

The higher $\alpha$, the more conditions need to be met to get the positive return (on top on not having Bank 2 default), and therefore the more complex the product.

Both products offer the same expected return, $R \times p$.

Increasing product complexity induces a cost $C$ to the bank, which is a convex function of $\lambda = \alpha R - R$, the additional return that the complex product offers in the good scenario. The rationale is that when structuring a retail structured product, Bank 2 add contingencies to a simple product, which initially offers the same return $R$ as in the product of bank 1 (we assume that banks have the same level of default risk). This cost represents structuring costs, but also potentially litigation and reputation costs associated with offering highly complex products to low sophisticated investors.

We assume that making the product complex increases the promised return, which becomes $R + \lambda$ at a cost $\frac{\lambda^2}{2}$.

## 4.2 Salient Thinkers

We assume that investors are salient thinker in the sense of Bordalo, Gennaioli and Shleifer (2012).

Consider the choice between the simple, and the complex product under Bordalo et al. (2012)'s framework. There are four states of the world, as products returns are not perfectly correlated:

$$S = (\alpha R, R), (0, R), (\alpha R, 0), (0, 0)$$

The ordering and diminishing sensitivity properties of the salience function suffice to imply that the salience ranking among states is:

$$\sigma(\alpha R, 0) > \sigma(\alpha R, R) > \sigma(0, R) > \sigma(\alpha 0, 0)$$

If and only if:

$$\alpha R - R > R \Leftrightarrow \alpha > 2$$

**Proposition 1** *For the complex product to be salient, the promised return that is offered in a complex product needs to be at least twice as large as the return offered by simple products.*

Note that this condition is unlikely to be met in a high interest rate environment, because the increase in $R$ obtained through increased complexity, for instance the sale of an option, is not a function of R. If selling an option on an index brings a premium of 2%, adding this feature can double the promised rate when interest rates are at 2%, but not when they are at 10%. When interest rates are low, this salience condition is easily achieved, as the premium of options is relatively bigger when compared to interest rates.

### 4.3 Transformed Probabilities

Let denote $\hat{p}$ and $\hat{p'}$ the transformed probability of getting the high return for respectively the simple and the complex products.

We know from Bordalo et al. (2012) that the decision weight attached by the salient thinker to the state where the complex product yields $\alpha R$ is:

$$\hat{p}' = \frac{p'(1-p)+p'p\delta}{\Sigma}$$

Where $\delta \in (0;1]$ and $\Sigma$ is the sum of the transformed probabilities of all the states of nature.

The decision weight attached by the salient thinker to the state where the simple product returns $R$ is:

$$\hat{p} = \frac{p(1-p')\delta^2+p'p\delta}{\Sigma}$$

Hence, the salient thinker evaluates the odds with which the complex product pays out relatively to the simple product as:

$$\frac{\hat{p}'}{\hat{p}} = \frac{p'}{p}\frac{(1-p)+p\delta}{(1-p')\delta^2+p'\delta}$$

We define as $K$ the coefficient of transformation of the odds

$$K = \frac{(1-p)+p\delta}{(1-\frac{p}{\alpha})\delta^2+\frac{p}{\alpha}\delta}$$

We have $K(1) > 1$, and:

$$\frac{\partial K}{\partial \alpha} = \frac{[(1-p)+p\delta]\times[\delta-\delta^2]\times\frac{p}{\alpha^2}}{[(1-\frac{p}{\alpha})\delta^2+\frac{p}{\alpha}\delta]^2} \geq 0$$

Therefore, we obtain the following proposition:

**Proposition 2** *As complexity increases, the transformed odds with which the complex product pays out relatively to the simple product increase.*

Complexity amplifies the deviation from the real probability of the salient thinker, by increasing the saliency of the high return.

## 4.4 Bank Profits

To make a profit, bank 2 can actually exploit the offer only a fraction $\theta$ of the promised return $\alpha R$ to the retail investor in the positive state of nature, with $\theta < 1$. Let $\Pi$ denote the profit of bank 2:

$$\Pi = \underbrace{pR}_{\text{Expected Return}} - \theta pR - C(\alpha) = pR(1-\theta) - C(\alpha)$$

Bank 2 can reduce the probability for the investor to receive the high return without her immediately preferring the simple product, because she overweights the probability of getting the promised return due to the saliency effect.

However, when fixing $\theta$, Bank 2 must insure that two constraints are satisfied.

- The *salience constraint*. Bank 2 needs to ensure the state $(\alpha\theta R, R)$ is still salient, relatively to the state $(0, R)$:

$$\alpha\theta R - R \geq R \Leftrightarrow \theta \geq \tfrac{2}{\alpha}$$

- The *valuation constraint*. Bank 2 has also to ensure that, under the condition that the promised return is salient, the complex product is still preferred to the simple product.

$$Kp\theta R \geq pR \Leftrightarrow \theta \geq \tfrac{1}{K}$$

Both these constrains limit how much profit Bank 2 can obtain from a given level of complexity.

The salience constraint is the one binding if and only if:

$$\begin{gathered} \tfrac{\alpha}{2} \leq K \\ \Leftrightarrow \tfrac{\alpha}{2} \leq \tfrac{(1-p)+p\delta}{(1-\frac{p}{\alpha})\delta^2 + \frac{p}{\alpha}\delta} \\ \Leftrightarrow \alpha \leq \tfrac{2(1-p)+p\delta+p\delta^2}{\delta^2} \end{gathered}$$

The right-hand side of the equation increases when $\delta$ decreases. Therefore, the more a salient thinker the investor is, the more likely it is that the salience constraint is the one binding.

## 4.5 Optimal Complexity

### *A. Assuming salient constraint is binding*

Let's first assume that the salient constraint is binding. Hence, $\frac{1}{\theta} = \frac{\alpha}{2}$

Bank 2's profit is:

$$\Pi = pR\frac{\alpha-2}{\alpha} - C(\alpha)$$
$$\Leftrightarrow \Pi = pR\frac{\alpha-2}{\alpha} - \frac{(\alpha R-R)^2}{2}$$

When we derive profits according to $\alpha$, we obtain:

$$\Pi'(\alpha) = pR(\frac{2}{\alpha^2}) - R^2(\alpha - 1)$$

### *B. Assuming valuation constraint is binding*

Let's now assume that the valuation constraint is binding. Hence, $\frac{1}{\theta} = \frac{(1-p)+p\delta}{(1-\frac{p}{\alpha})\delta^2+\frac{p}{\alpha}\delta}$

Bank 2's profit is now:

$$\Pi = \frac{pR}{1-p+p\delta}\left(\frac{-p}{\alpha}(\delta-\delta^2) + (1-p) + p\delta - \delta^2\right) - C(\alpha)$$
$$\Leftrightarrow \Pi = \frac{pR}{1-p+p\delta}\left(\frac{-p}{\alpha}(\delta-\delta^2) + (1-p) + p\delta - \delta^2\right) - \frac{(\alpha R-R)^2}{2}$$

When we derive profits according to $\alpha$, we obtain:

$$\Pi'(\alpha) = pR(\frac{\gamma}{\alpha^2}) - R^2(\alpha - 1)$$

with $\gamma = \frac{p(\delta-\delta^2)}{1-p+p\delta}$. We observe that $\gamma \in [0;1]$.

### *C. Optimal Complexity*

The first order condition is:

$$\alpha^3 - \alpha^2 - \frac{\beta p}{R} = 0$$

with $\beta = 2$ when the salient constraint is binding, or $\beta = \gamma$ when the valuation constraint is binding.

This polynomial function of $\alpha$ has a unique positive solution $\alpha^*$, which is derived in the appendix by applying the formula of Cardan (1573):

$$\alpha^* = \left((\frac{1}{27} + \frac{\beta p}{2R}) - \sqrt{(\frac{1}{27} + \frac{\beta p}{2R})^2 - \frac{1}{27^2}}\right)^{1/3} + \left((\frac{1}{27} + \frac{\beta p}{2R}) + \sqrt{(\frac{1}{27} + \frac{\beta p}{2R})^2 - \frac{1}{27^2}}\right)^{1/3} + \frac{1}{3}$$

We have $\frac{\partial \alpha^*}{\partial R} \leq 0$ (see Appendix).

Finally, the optimal level of complexity $\overline{\alpha}^*$ that the bank chooses is:

$$\overline{\alpha^*} = Max\Big(Min\big(\alpha^*_{\beta=2}; \tfrac{2(1-p)+p\delta+p\delta^2}{\delta^2}\big); \alpha^*_{\beta=\gamma}\Big)$$

Therefore, we obtain:

**Proposition 3** *The lower the return $R$ offered by the simple product is, the higher the optimal level of complexity $\overline{\alpha^*}$ is.*

$R$ largely depends on the interest rate environment (and on the default probability of banks). Hence, when interest rates are low, the optimal level of complexity is higher.

$\alpha^*$ is increasing in $\beta$. As $\gamma \leq 2$, we conclude that the optimal level of complexity is higher when the salient constraint is binding $\Rightarrow$ when investors are more salient.

**Proposition 4** *The optimal level of complexity is higher when investors are more salient thinker.*

Finally, when we substitute $\alpha$ by its optimal value $\overline{\alpha^*}$ in the profit function, we observe that profits increase when $R$ decreases

**Proposition 5** *The profit of the bank offering the complex product increases when the return $R$ offered by the simple product decreases.*

## 4.6 Empirical Predictions

Our theoretical framework allows us to develop a series of testable empirical prediction:

- **Complexity and promised return**: The promised return $\alpha R$ is an increasing function of $\alpha$ (Complexity)

- **Complexity and bank profits**: Bank profit is an increasing function of $\alpha$

- **Complexity and *ex post* return**: As bank capture a higher profit with complex products, *ex post return* should be decreasing with complexity

- **Complexity and interest rates**: Complexity should be higher when interest rates are low. In the cross-section of banks, this translates into banks with lower funding costs should offer more complex products.
- **Complexity and investor type**: Complexity is higher when banks target more salient thinkers.
- **Complexity and competition**: Competition should amplify rather than mitigate the use of complexity, as bank compete on the promised return, and not on the expected return.

# 5 Empirical results

The following section provide empirical tests of the empirical predictions established in the previous section.

## 5.1 Complexity and Promised Return

We first analyze the promised return offered by structured products, defined as the basic rate that results from their primary structure. The promised return is highlighted in the marketing strategy, as observed in the marketing leaflets included in our data (see the example in the online appendix). Consistent with our theoretical framework, we find that more complex products offer higher promised returns.

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 promised return 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 promised return and level of complexity by regressing the former on the latter using each of our alternative measures and including the usual controls. Table III presents the coefficients of these regressions. The promised return 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 III

## 5.2 Complexity and Profitability

We then test whether more complex products offer higher markup to the banks distributing them. 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. We apply this methodology to a subsample of products indexed to the most frequent and most liquid underlying in our sample, the Euro Stoxx 50 index.

### *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 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,

[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.

[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

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

### *C. Results*

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.[20] [21]

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

$$YearlyMarkup_i = \alpha \times \#\ \mathit{Features}_i + \delta_y + \eta_c + \gamma \mathit{Credit\ Risk}_i + \epsilon_i \tag{2}$$

where $YearlyMarkup$ is the difference between issuance price and fair value, estimated as detailed in section 2, normalized by product maturity, $\#\mathit{Features}$ is the number of payoffs embedded in the structured product formula as a measure of its complexity, and $X_i$

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.

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

[21] 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.

is a vector of product level controls. A dummy, $CreditRisk$, indicates non-collateralized products like bonds and deposits. Because these products provide funding to the issuer, this specificity must be taken into account when assessing profitability.[22]

INSERT TABLE IV

Table IV 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.[23] [24] 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.[25] Although

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

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

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

[25] 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.

### 5.3 Complexity and Ex-Post Performance

We now examine 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.[26] 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,

$$YearlyPerf_i = \alpha \times Complexity_i + \beta \times Capital\ protection_i + \gamma Credit\ Risk_i + \gamma_a + \delta_y + \eta_c + \epsilon_i \tag{3}$$

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 $\delta_y$, $\eta_c$, and $\gamma_a$ 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 V

Table V presents the estimated coefficients of the regression for our three measures of complexity. The three specifications indicate a significant negative correlation between

[26] 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.

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.

## 5.4 Complexity and Underlying Interest Rate

Turning to the funding costs, which directly affect the interest rate banks can pay on short and long term deposits, we test whether banks with low funding costs, which therefore cannot offer high paying deposits, offer more complex products than banks with higher funding costs.

We regress product complexity on the level of distributors' CDS spread as a proxy for funding cost. For this analysis, we restrict the analysis to banks that have a listed CDS. The CDS spreads used are from Datastream for the period 2007-2010. Table VI displays the regression coefficients for our three measures of complexity. We include quarter fixed effects to control for changing market conditions. We indeed find that product complexity is negatively correlated with the level of the distributing bank's CDS spread. Results are robust to using the three measures of complexity.

INSERT TABLE VI

## 5.5 Complexity and Investor Type

We then explore the relationship between a product's level of complexity and the type of the bank marketing it. Savings banks provide financial services primarily to rural and low- to middle-class households, which are more likely to be salient thinkers (Solomon et al. (2014), Stango and Zinman (2014)). We group distributors into four categories: savings banks, commercial banks, private banks/wealth managers, and others.[27] Table 1 in the

[27] 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).

online appendix describes and identifies the types of the 20 main distributor groups in 2010.

Table VII 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. We confirm these unconditional statistics by regressing product complexity on distributor type dummies, controlling for product characteristics. The second panel in Table VII 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 VII

## 5.6 Complexity, Number of Competitors and Market Differentiation

We finally examine the level of complexity, and differentiation, relative to the number of competitors in the market, to test whether banks competing on promised return indeed leads to a rise in complexity when competition intensifies. Differentiation increases the difficulty to compare the actual total payoff formula, and therefore fosters comparison of the promised return. We use panel data at the country and distributor level spanning 15 countries and 471 distributors.[28]

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

[28] 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.

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.[29]

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

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

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, $\theta_c$, to control for time invariant market specificities (e.g., size), and year fixed effects, $\delta_y$, 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.[30] 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

[29]Using equally weighted averages yields comparable results.

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

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

# 6 Alternative Motives for Issuing Complex Securities

In this section, we discuss potential alternative motives for issuing complex securities.

## 6.1 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.

## 6.2 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.[31] 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 the hypothesis that the retail structured product market essentially targets households that want to gamble.[32]

## 6.3 Confusing Retail Investors

Banks may use complexity to intentionally confuse retail investors, and extract rents from them. 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)). Some of our results are also 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. Ellison (2005), Gabaix and Laibson (2006) and Carlin (2009)'s models of consumer obfuscation predict that more complex products are more profitable for the distributing firms. This result is also potentially consistent with banks intentionally inducing confusion by resetting households' possible learning (Carlin and Manso

[31] 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.

[32] 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.

(2011)). However, this framework does not convincingly explain the level of complexity observed in the market, as a limited amount of complexity should be enough to confuse the majority of investors

Second, 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.[33]

# 7 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 issuing complex financial products.

We investigate the evolution of product complexity 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, and find that product complexity has significantly increased over time. We further observe that the exposure to downside risk embedded in these structured products, as well as the level of product differentiation, have increased during our sample period.

We apply the saliency theoretical framework from Bordalo et al. (2012) to our market and develop a series of empirical prediction that we subsequently test in our data.

We find that the promised return of a retail structured product is positively correlated with its complexity. We also investigate the relationship between complexity and product profitability. 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.

We also find distributors that target low-income investors, who are more likely to be

[33]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.

salient thinkers, to offer relatively more complex products. Additionally, banks with low funding costs offer more complex products than banks with high funding costs, which is consistent with banks competing on the promised return of investments.

Additionally, our study suggest that competition amplifies rather than mitigates migration towards greater complexity. Indeed, average complexity and product differentiation increases when 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 however largely consistent with banks catering to households seeking high yield in a low interest environment, and potentially with an obfuscation motive. 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)).

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# A Figures

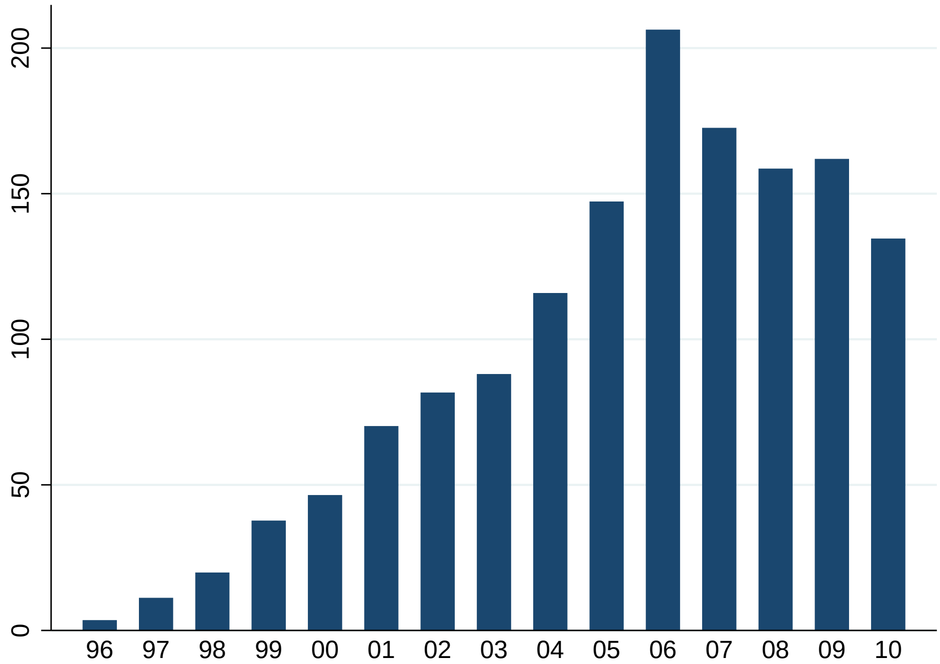


**Figure I. Volume Sold per Year, in billion euros**
This figure shows, in billions of euros, volume issuance of tranche retail structured products in the European market over the 1996-2011 period. The countries include Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Hungary, Ireland,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

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

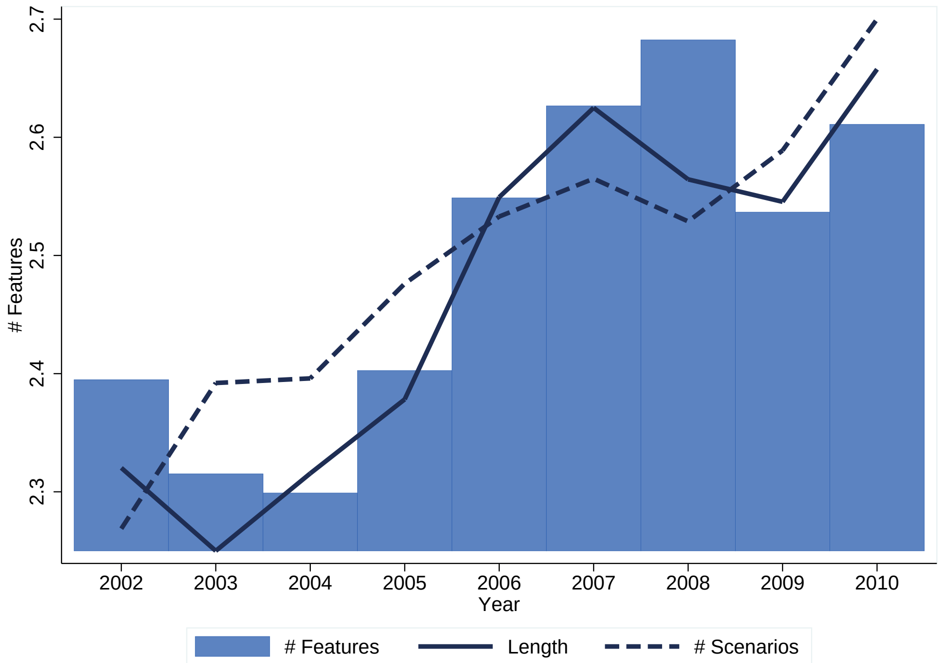


**FIGURE IV. Predicted Product Complexity by Year**

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.

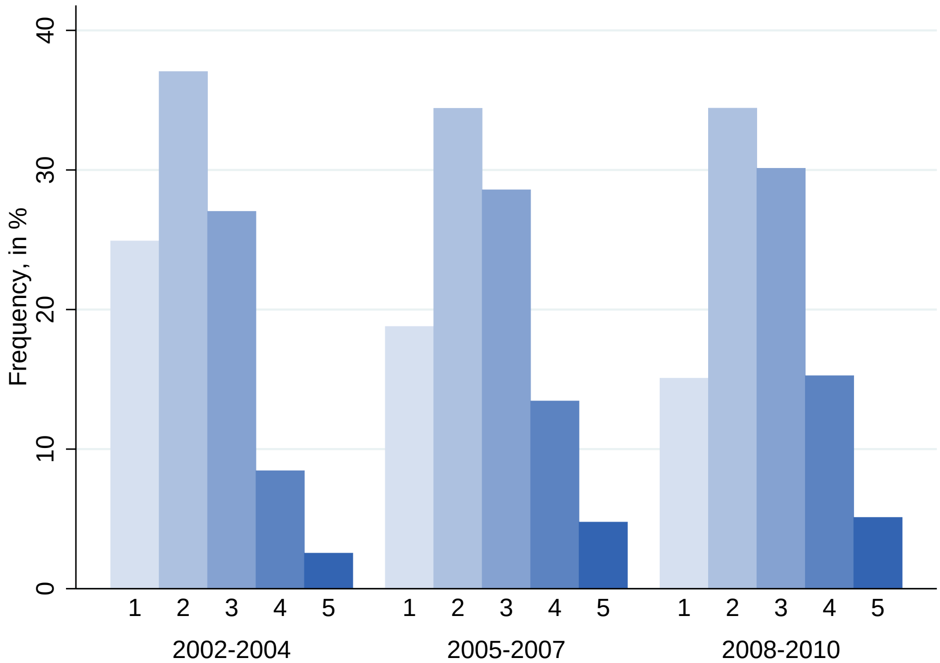


**FIGURE V. Evolution of the Distribution of Product Complexity**

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).

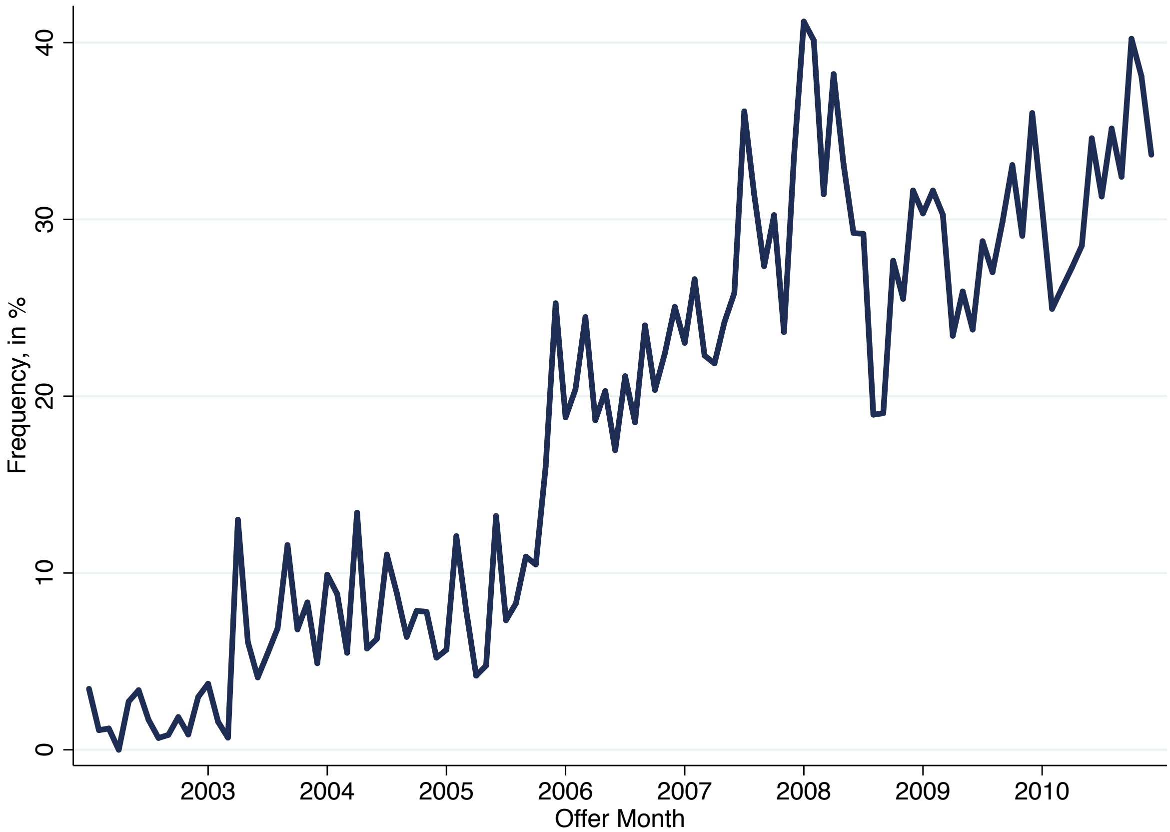


**Figure VI. Ratio of Products Exposed to Downside Risk**

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.

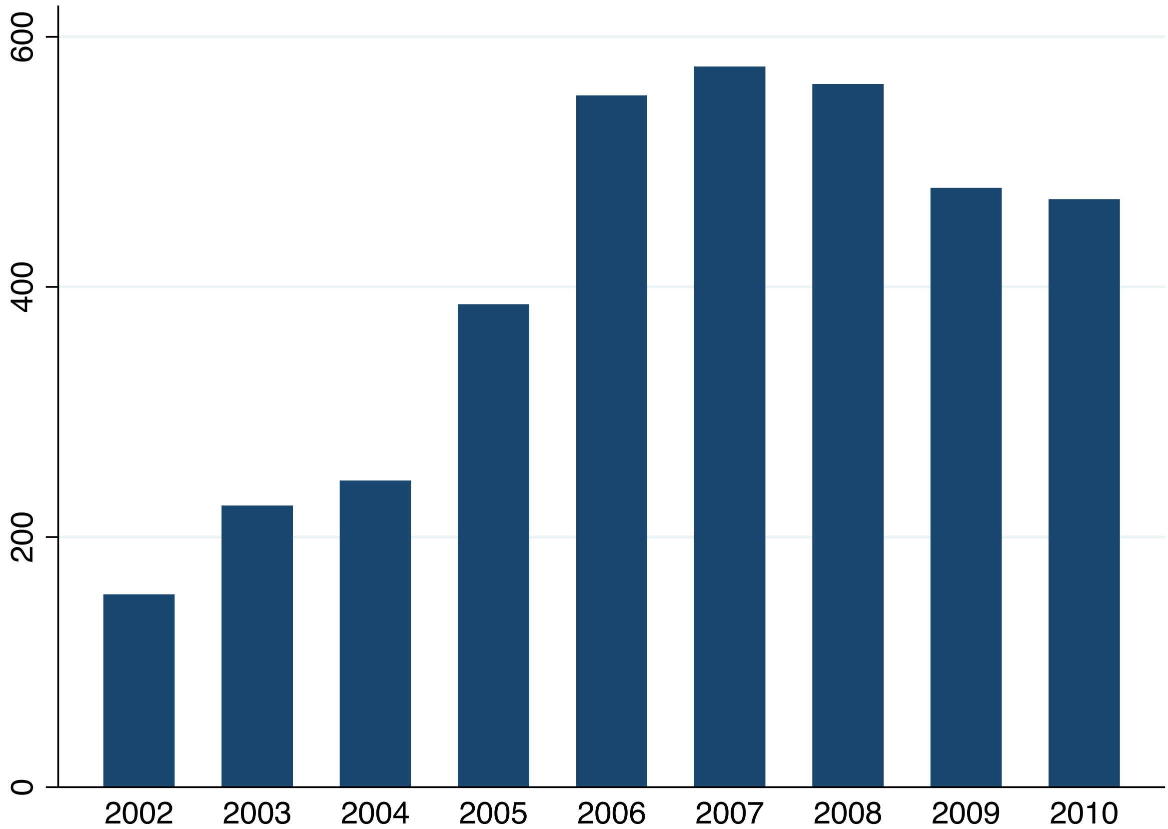


**FIGURE VII. Evolution of Product Differentiation**

This figure shows the evolution of the number of types of product marketed over the 17 countries of our sample by year. A type of product is defined as a given combination of feature, as described in section 2.

# 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 Promised Return

| | **Promised Return, 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. *promised return* 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 IV. 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 V. 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 VI. Product Complexity and Issuer Funding Cost

| | # 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 VII. 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 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.

# 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.

*Promised Return*: 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.