CATERING TO INVESTORS THROUGH SECURITY DESIGN: HEADLINE RATE AND COMPLEXITY *

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Abstract

This study investigates how banks design financial products to cater to yield-seeking investors. We focus on a large market of investment products targeted exclusively at households: retail structured products. These products typically offer a high return under their best-case scenario –the headline rate– that is nested in a complex payoff formula. Using a text analysis of the payoff formulas of the 55,000 products issued in Europe from 2002 to 2010, we measure product headline rates, complexity and risk. Over this period, product headline rates depart from the prevailing interest rates as the latter decrease, complexity increases, and risky products become more common. In the cross section, the headline rate of a product is positively correlated with its level of complexity and risk. Higher headline rate, more complex, and riskier products, appear more profitable to the banks distributing them. Our results suggest that financial complexity is a by-product of banks catering to yield-seeking investors.

Keywords: Catering, Financial Complexity, Shrouding, Reaching for Yield, Household Finance, Structured Product *JEL codes*: I22, G1, D18, D12

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1 Introduction

Since the end of the 1990s, European financial institutions have designed, marketed and sold more than 2 trillion euros of complex financial products to households, the so-called *retail structured products*. More recently in the US, equity-linked certificates of deposit, one category of retail structured products that are not SEC-regulated, are becoming increasingly popular. The marketing of these products, whose payoffs are defined ex ante as a function of an underlying asset performance, typically focuses on the return they offer under the best-case scenario: the *headline rate*. For example, the product "Fixeo", sold in 2010 by Credit Agricole with a volume larger than 50 million euros, offers a headline rate of 8% if a set of conditions is satisfied:

> *This is a growth product linked to the DJ Eurostoxx50. After 1.5 years of investment, if the level of the index is at or above its initial level, then the product terminates on that date and offers a capital return of 112% at that time. At maturity, the product offers a capital return of 124%, as long as the final index level is at or above its initial level. Otherwise, the product offers a capital return of 100%, as long as the final index level is at or above 60% of its initial level. In all other cases, the product offers a capital return of 100%, decreased by the fall in the index over the investment period.*

The global development of this innovative class of complex assets raises the question of the determinants of security design.

While innovation in the design of financial products is traditionally seen as a way to improve risk sharing (Allen and Gale, 1994; Duffie and Rahi, 1995), banks may also introduce innovative product features to cater to yield-seeking households (Bordalo et al., 2016). Doing so raises a challenge for banks: higher yields come with higher risk, while households are, on average, risk averse. Complex designs for financial securities may allow banks to circumvent household risk aversion by turning their attention to the headline rate, while shrouding risk. This paper investigates whether complexity in retail finance is a by-product of banks catering to the yield appetite of households.

Retail structured products represent an ideal laboratory to address the determinants of security design. First, as they are structured with derivatives, these products offer a unique flexibility in terms of design to the banks selling them. Second, their payoff formula, defined ex ante, allows us to objectively measure the headline rate, complexity, risk and profitability, and investigate how these characteristics relate to each other. Third, this market is large, with more than one trillion dollars in assets under management in Europe only, and is currently growing in Asia and in the US.

This study introduces a novel dataset containing comprehensive information on all *core* retail structured products sold in Europe between 2002 and 2010, totaling more than 1.3 trillion euros of issuance.[1] The database hence covers approximately 55,000 products issued across 16 different countries by more than 400 distributors. These data include detailed product characteristics, such as information on distributors, underlying assets, maturity, and volumes sold, and most importantly, a detailed textual description of the payoff formula translated into English by the data provider, as in the "Fixeo" example.

We collect the product headline rate and measure product complexity and risk through an algorithmic text analysis of the product payoff descriptions. We first identify the headline rate by flagging specific combinations of keywords and numerical values. With a similar methodology, we then identify payoff features that are embedded in the payoff formula of a product. We count these features to build our main measure of product complexity. This measure accounts for the multi-dimensionality of contracts offered in the retail market for structured products. The more dimensions a product has, the more difficult it is for a retail investor to understand and compare the product with other products. Finally, we measure product risk with an indicator variable on whether the product exposes investors to a complete loss of the investment.

[1] *Core* products represent 90% of the total volume of retail structured products.

Armed with these measures of headline rate, product complexity, and risk, we document three major trends in the retail market for structured products over our sample period. First, headline rates depart from the level of interest rates when interest rates decrease. Second, product complexity increases significantly, with no discernible drop during the global financial crisis. Third, the fraction of products exposing investors to complete losses increases significantly.

We then explore in details the determinants of the design of retail structured products. First, we find that products offering high headline rates are both riskier and more complex. Second, the spread between product headline rates and interest rates increases when interest rates are low, along with product complexity and risk. Third, both products offering high headline rate and more complex products yield higher markups to the banks that issue them. These *ex ante* higher markups translate into lower *ex post* performance for more complex products. Finally, we explore the cross-section of banks distributing retail structured products, and find that savings banks, which mainly target lower-income households, offer more complex products than commercial banks do. Banks prone to risk taking, such as highly leveraged banks or banks exposed to Greek sovereign bonds, also distribute more complex products.

We discuss our empirical findings in light of two theories of the determinants of security design: first, tailoring securities to improve risk sharing (Allen and Gale, 1994; Duffie and Rahi, 1995) and second, catering to yield-seeking investor by shrouding risk (Bordalo et al., 2016; Gabaix and Laibson, 2006). The increasing level of complexity we observe, as well as its correlation with product risk and headline rates, can be reconciled with both theories. However, both the higher headline rates and complexity when interest rates are low, and the higher profitability of complex products, are only consistent with a catering rationale. Our empirical results are therefore suggestive of an interplay between investors' salient thinking and banks' shrouding strategy (Inderst and Obradovits, 2016).

Our work adds to several strands of the literature. First, our study contributes to the literature on reaching for yield (Rajan, 2011; Yellen, 2011; Becker and Ivashina, 2015; Hanson and Stein, 2015). It also complements the research on catering to investor biases, both from corporate issuers (Baker and Wurgler, 2002; Baker et al., 2009; Greenwood et al., 2010) and from financial firms (Harris et al., 2015; Luo, 2016).

Second, the present study complements research on the dark side of financial advice provided to retail clients (Inderst and Ottaviani, 2009; Anagol et al., 2015; Bergstresser and Beshears, 2010; Hackethal et al., 2012; Karabulut, 2013; Hoechle et al., 2015; Foerster et al., ming; Gennaioli et al., 2015) and of financial institutions' marketing strategies in retail finance. Schoar and Ru (2016) show that credit card companies exploit behavioral biases of households through their reward programs. Sun (2014) provides evidence of mutual funds increasing their fees in less price-sensitive segments of the market.

Finally, our work contributes to the growing literature on complex securities and structured products (Griffin et al., 2014; Ghent et al., 2016; Carlin et al., 2013; Amromin et al., 2013; Sato, 2014). Hens and Rieger (2014) theoretically show that the most popular retail structured products do not bring additional utility to rational investors. On the basis of a detailed analysis of 64 issues of a popular structured product, Henderson and Pearson (2011) estimate overpricing by banks to be nearly 8%.

The rest of our paper proceeds as follows. Section 2 describes the background of the retail market for structured products in Europe and the data we use. Section 3 explains the methodology for measuring headline rates, complexity, product risk, and markups. Section 4 documents basic facts in the retail market for structured products and Section 5 explores the determinants of product design. Section 6 discusses our empirical findings in light of two theoretical frameworks. Finally, Section 7 concludes.

2 Retail Structured Products: Background and Data

2.1 Market Background and Regulatory Framework

Retail structured products include any investment products marketed to retail investors and possessing a payoff function that varies automatically and non-linearly with the performance of an underlying financial asset.[2] Typically designed with embedded options, these products leave no room for discretionary investment decisions during the life of the investment.[3] These products are based mainly on equity indices and individual stocks but may also offer exposure to commodities, fixed income, or alternative indices.

The retail market for structured products emerged in Europe at the beginning of the 2000s and has subsequently experienced steady growth. In 2012, with 770 billion euros of assets under management, the retail market for structured products stood at 3% of all European financial savings, one-eighth of the mutual fund assets under management in Europe, and double the assets under management of the hedge fund industry.[4] The European market is the largest market in the world, with more than half of the global volume. The US and Asian markets, however, have been growing fast: retail structured product assets under management exceeded 400 billion US dollars in 2015 in the US.[5]

In Europe, retail structured products are available to any household and are under the same regulatory framework as stocks or mutual funds during our sample period. Specific rules to regulate the distribution of these products are rare: while Italy in 2009, France in 2010, and Belgium in 2011 tightened the conditions under which certain categories of structured products could be sold to retail investors, Norway was the only country that placed a ban on selling structured products to retail investors and did so in 2008.[6,7]

[2] Exchange traded funds, which have payoffs that are a linear function of a given underlying financial index, are not retail structured products.

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

[4] Source: ESMA (2013).

[5] Source: Starr (2015) $https://www.sec.gov/news/speech/speech-amy-starr-structured-products-.html$.

[6] Source: 2008 Annual Report of the Supervisory Authority of Norway.

[7] In 2009, Italy tightened the conditions under which insurance companies could issue index-linked contracts. In 2010, the French Market Authority limited to three the number of features that could be embedded in the payoff formula of a structured product if and only if the capital is at risk (source: $http://www.amf-france.org/documents/general/9662_1.pdf$). In 2011, the Belgian Financial Services and Markets Authority called upon the financial sector not to distribute to individual investors structured products that are considered particularly complex on a voluntary basis (source: $http://www.fsma.be/en/Doormat/Consultations/Cons/Article/press/div/2011-08-12_consult.aspx$).

The general applicable regulatory framework, driven mainly by investor protection concerns, is defined at the European Union level by two main directives: the European Directive (1985, 2001, 2011) on Undertakings for Collective Investment in Transferable Securities (UCITS) and the 2007 Markets in Financial Instruments Directive (MiFID). The European UCITS Directive regulates information disclosure for any investment product.[8] However, anecdotal evidence from litigation suggests that these disclosure requirements may not be effective at reducing information asymmetry between distributors and retail investors.[9] The 2007 MiFID affects the retail market for structured products by requiring distributors to disclose commercial and management fees, which may have increased the incentives to hide markup within the structure of financial products. This directive also introduces suitability and appropriateness tests for complex products. These tests, however, do not cover the vast majority of retail structured products, as they hold a UCITS format and therefore, are considered "non-complex" under the 2007 MiFID.[10,11]

In comparison to Europe, the US regulation of retail structured products is more stringent: only qualified investors, with at least 1 million US dollars in net worth can invest in *non-registered* products, which, until now, have represented the bulk of retail structured products in the US. In addition, the small fraction of structured products that are *registered* are subject to the Securities and Exchange Commission (SEC) supervision, which puts strict conditions on the type of information that can be used for marketing purposes. By contrast, in Europe, the creativity of the marketing brochures of these products is a key feature of the market (see Figures A1, A9, and

[8]The 2011 Directive has extended this information disclosure by asking for systematically shown back-testing.

[9]The Caisses d'Epargne (Doublo'Monde, 2004) and BNP Paribas (Jet 3, 2001) in France, UBS in the United States (structured notes linked to the V10 index, 2009 and 2010), and Santander in Spain, among others, have been fined for misleading investors in the sale of structured products. In addition, in September 2008, in Switzerland, the default of Lehman Brothers brought about several litigation cases because retail investors lost their full initial investment in 700 million Swiss francs of "capital guaranteed" products. Sources: Les Echos, Financial Times, SEC website.

[10]The forthcoming MiFID 2 directive considers structured products as complex.

[11]Measuring the exact effect of the application of the first MiFID on the retail market for structured products is challenging for several reasons: the application is contemporaneous with the global financial crisis and the directive was applied almost simultaneously across different European countries, and most importantly, across different types of investment products.

A10 in the Appendix). Bethel and Ferrel (2007) detail the US legal framework for retail structured products prior to the Dodd–Frank Wall Street Reform and Consumer Protection Act. However, this stringent US regulation is currently facing a challenge: structured certificate of deposits, which are not regulated by the SEC as they are not considered to be securities, have been gaining popularity in the US in recent years.

2.2 Dataset

Our analysis is based on a comprehensive dataset of European retail structured product issuances between 2002 and 2010.

We obtain our data from a commercial data provider (which we label "the platform") that collects detailed information on all retail structured products sold in Europe. This database is the main source of data for retail structured product distributors, financial media, and regulators, including the SEC, the International Organization of Securities Commission, the Financial Industry Regulatory Authority (FINRA) and the European Securities and Markets Authority (ESMA).[12] The platform gathers issuance data from two main sources: national regulators, when information is subject to regulatory disclosure requirements, and market players, which collectively share information through this database.[13] Since no product has ever been removed from the dataset once it has been included, these data are not subject to survivorship bias. Cross-validation with practitioner documents reporting the aggregate number of issuances and volume, and country-level comparisons with other academic studies, indicate that the database provides excellent coverage of the industry. 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).

Within the retail market for structured products, we restrict attention to the largest category of products in terms of volume: *core* products. These products have a fixed maturity, are non-standardized, and are offered during a limited period, typically

[12] Corporate clients of the platform include, among others, JP Morgan, Barclays, Credit Suisse, and Commerzbank.

[13] Some distributors ask the platform to disclose certain information, such as issuance volumes, only at an aggregate level.

4 to 8 weeks. *Core* products represent 90% of the total volume of retail structured products as per the data collected by our provider.[14] Retail investors investing in these products typically follow a buy-and-hold strategy owing to the significant penalties for exiting prior to maturity.[15] Information on volume sold is available at the issuance level for more than 60% of total volume, and at the distributor-year level for the whole market after 2006. We use the information at the distributor-year level to fill in the issuance volume variable when it is missing, using the average volume for each distributor in a given year.[16]

In addition to standard issuance data, the dataset provides, for each product, a concise text that precisely describes in English the final payoff formula, based on the same consistent methodology over the years. This payoff description is crucial to our analysis as it allows us to collect the headline rate, and to measure product complexity and risk, as described in Section 3. Finally, the platform collects the final payoff of the products at maturity, which is equivalent to the overall ex-post performance for the products that do not have intermediate cash flows. The coverage for this information is not exhaustive: it is available for 46% of the products that have matured and have no intermediate cash flows in our sample.

The dataset we obtain initially includes 68,433 issuances of core products from the 18 European countries.[17] Each issuance is identified uniquely by its ISIN code, as required by European regulation. After filtering, our final dataset consists of detailed information on 53,541 core retail structured products issued between 2002 and 2010 in 16 European countries, for an estimated volume of 1.45 trillion euros of cumulative

[14]Therefore, we exclude from our analysis 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, such as warrants and turbos. Flow products, which include bonus and discount certificates, are popular mainly in Germany, with hundreds being issued daily and 825,063 from 2002 to 2010. The average volume, however, is only 20,000 euros, compared with 8.8 million euros for the core market we consider.

[15]The buy-and-hold strategy of these products with a maturity of up to 10 years may explain why reputational concerns have not been binding on this market, as opposed to the security market in the 1920s (Kroszner and Rajan (1994)). Most of the time the performance is revealed only when the product matures.

[16]The average is computed after excluding products with disclosed volumes.

[17]These countries are, by market size, Italy, Spain, Germany, France, Belgium, the United Kingdom, the Netherlands, Sweden, Portugal, Austria, Denmark, Ireland, Norway, Finland, Poland, the Czech Republic, Hungary, and Slovakia.

issuance.[18,19]

We complement this dataset with financial information on structured product distributors from Bankscope and the European stress test dataset, and classify the distributors based on information from their websites into three categories: commercial banks, private banks, and savings banks. In addition, we gather information on market conditions at the time of issuance, such as interest rates and volatility data.

2.3 Product Main Characteristics

A retail structured product is defined along four main dimensions: the underlying financial asset, payoff formula, maturity, and format. Table A1 in the online appendix provides summary statistics on the main characteristics of a retail structured product. Equity is the most frequent underlying asset class: these products rely predominantly on a single stock, single index, basket of shares, or basket of indices. However, the share of products indexed to other asset classes, such as interest rates or commodities, increased over the sample period. In terms of the payoff formula, the product's primary feature is typically a call, which allows the investor to participate in the rise of the underlying financial index, or a pure income product, which pays a fixed coupon. These primary features are frequently associated with additional features, such as a reverse convertible or cap (see Table A7 in the online appendix for a definition of each of the payoff features). The maturity of a structured product is 4.2 years on average and ranges from less than 1 year to more than 10 years.

While retail structured products are designed by investment banks, they are sold mostly to households by commercial banks (71% of the volume), with savings banks (16%) and private banks (10%) also having significant shares of the market. Cumulative volumes per country since the market's inception, as well as penetration

[18]This compares with samples covering 1,588 products, one country, and 50 billion US dollars of issuance in Henderson and Pearson (2011).

[19]We implement the following filtering: we drop countries that have had less than 1 billion euros in issuance since market inception (Hungary and Slovakia), and are left with 16 European countries and 68,135 issuances. Then, we drop issuance data prior to 2002, as these data were back-filled by our data provider, and therefore, are subject to potential bias (this removes 10,018 observations). Finally, we drop observations whose payoff descriptions are empty or cannot be exploited for our purpose of measuring complexity (4,576 observations).

statistics, are reported in Table A3 of the online appendix. Italy, Spain, Germany, and France dominate in terms of volumes sold, jointly constituting 60% of the total market. Alternatively, the countries where structured products represent the highest share of financial wealth are Belgium (8.5%), Austria (3.3%), and Portugal (3.2%). Figure I shows that the issuance volume have been increasing at a rapid pace since market inception, with only a small decrease after the global financial crisis.

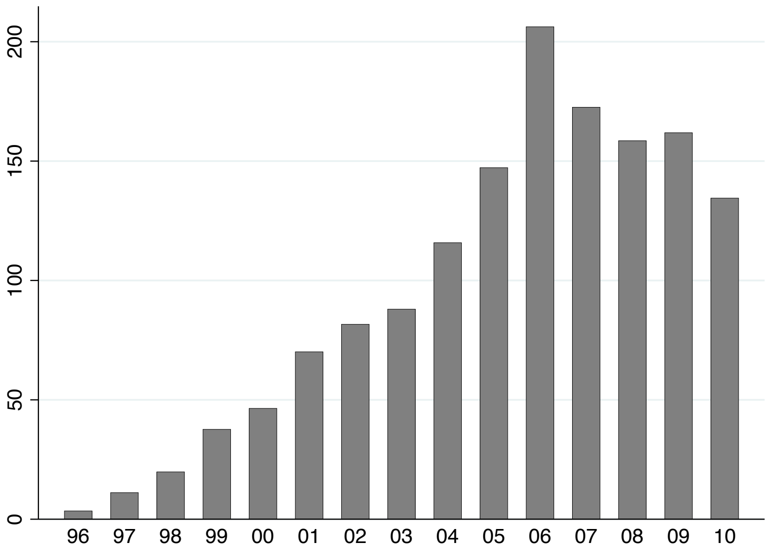

FIGURE I. Volumes Sold per Year

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

2.4 Product Marketing

Both the product design and marketing schemes of retail structured products typically highlight a headline rate. This headline rate corresponds to the yearly return the investor will receive in the best possible scenario. For instance, Figure II displays the net payoff diagram of a product marketed in 2009 in Germany, Austria, Spain, the Netherlands, and Belgium by Commerzbank. The product includes a digital payoff with a reverse convertible feature, which offers a yearly coupon of 6.2% and a 100% capital return at maturity if the final performance of the underlying is positive, but

100% participation in the negative performance of the underlying if its final level is below 70% of its initial level. The headline rate is therefore 6.2%, and is included in the product name, "6.2% Reverse Exchangeable Total", which illustrates Commerzbank's strategy to make it salient.

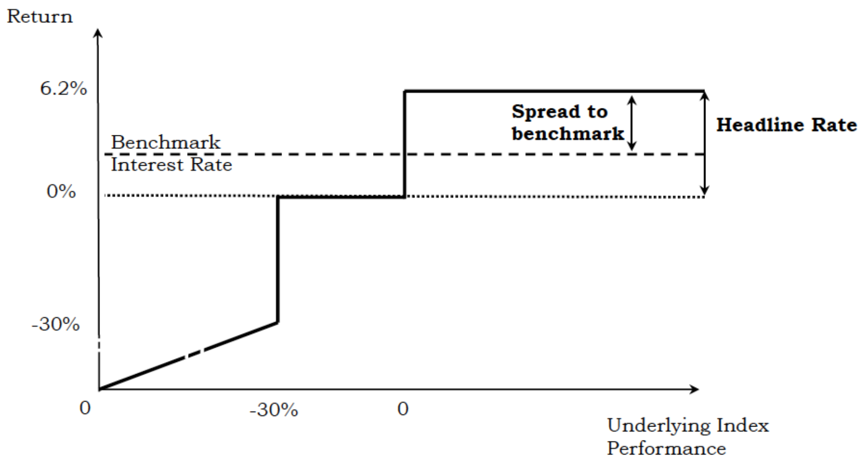

FIGURE II. Example of a Retail Structured Product Payoff

This diagram presents an example of a retail structured payoff and displays its related headline rate. The product offers a yearly coupon of 6.2% and a 100% capital return at maturity if the final performance of the underlying is positive (Eurostoxx 50) but 100% participation in the negative performance of the underlying asset if its final level is below 70% of its initial level.

Financial institutions appear to rely frequently on analogies and powerful metaphors in the marketing material of retail structured products, to draw investor's attention to the headline rate. This marketing strategy facilitates the association of positive attributes with structured products ((Mullainathan et al., 2008; Zaltman, 1997)). Figure A1 in the online appendix provides two examples of the front pages of brochures marketing retail structured products that follow this rationale. The diversity and creativity of product names also illustrate this marketing strategy. Table I provides the distribution of the analogies invoked by the names of all retail structured products sold in France from 2002 to 2010. The table shows that virtually all product names are related to one key metaphor stressed by Zaltman (1997): transformation, journey, balance, or resource. Each metaphor is characterized by a positive attribute. The objective is to persuade the investor to assess positively the quality of the product through the transfer of these positive attributes from the metaphor to the structured product itself. For example, the name "Elixir" associates the product with a resource and suggests that the investor will access magical power when investing in this product.

Table I. Retail Structured Product Names in France: Key Analogies

Key Analogies *(%)*	**Transferred Attributes *(%)***	**Examples**
Transformation (32 %)	Vitality (11%)	*Dynamic, Elanceo, Energetic, Expansia*
	Amplification (9%)	*Maximizer, Melioris, Optimiz, Digimax*
	Success (6%)	*Winner, Best seller, Emeritus, Star*
	Multiplication (6%)	*Double top, Triple horizon*
Balance (25 %)	Security (18%)	*Guarantee, Amareo, Locker, Serenity*
	Robustness (5%)	*Strength, Magnesium, Lion, Protein*
	Stability (1%)	*Beau fixe*
Journey (24 %)	Unchartered Territories (6%)	*Archipel, Chamsin, Wapiti, Jayanne*
	Aventure (4%)	*Conquistador, Drakkar, Cruzador*
	Alpinism (2%)	*Cordillera, Hight, Hiking, Yeti*
	Mythology (2%)	*Izeis, Goliath, Keops, Nemea*
	Cap (1.4%)	*Objective, Cap, Horizon*
	Exotic Culinarity (1.2%)	*Capuccino, Pimento, Lion, Cardamone*
Resource (19 %)	Virtuosity (6%)	*Allegro, Arpeggio, Bolero, Harmony*
	Privilege (5%)	*Four stars, Diamond, Quartz, Signature*
	Magic (4%)	*Prism, Filtreo, Elixir, Hologram*
	Opportunity (2%)	*Opportunity, Declic, Atout*
	Sport (2%)	*Sprint, Tie Break, Triathlon*
	Strategy (1.2%)	*Strategy, Selection, Allocator*
	Precision (1%)	*Metronom, Autofocus, Zoom*
	Science (1%)	*Alpha, Elipse, Isocel, Philosophy*
	Innovation (0.7%)	*Digiteo, Primio, Inedit*

This table provides the frequency of key analogies and transferred attributes used in the names of French retail structured products. The typology of analogies is from Zaltman (1997). The sample covers all products issued in France from 2002 to 2010.

3 Constructing the Variables of Interest: Headline Rate, Complexity, Risk, and Markups

3.1 Collecting the Headline Rate

We collect the headline rate of *coupon* retail structured products through a text analysis algorithm that scans the textual description of each payoff formula.[20,21] The code for the text-analysis algorithm is available in the online appendix. We manually check and improve the accuracy of our algorithm by iterating repeatedly on random subsamples of 100 products until we reach a level of reliability of 95%. See Table A2 in the online appendix for the descriptions of the top three blockbuster products per country and corresponding headline rates.

3.2 Measuring Payoff Complexity

We develop three measures of the complexity of the payoff formula. As the "Fixeo" example in the introduction illustrates, the payoff formula is the main source of product complexity in this market.[22]

Our three measures of complexity are derived from the text description of the product payoff formula provided by the platform. This payoff description translates into English the required information needed to calculate product performance at maturity. The platform presents retail structured product prospectuses consistently

[20] Coupon products pay a fixed amount each period, or at maturity, conditional on the performance of the underlying asset, and represent more than half of the retail structured products issuances, the rest being participation products. Participation products offer a participation in the positive performance of the underlying asset, typically under certain conditions.

[21] For participation products, the closest equivalent to headline rate would be the level of participation in the best scenario, multiplied by the expected return of the underlying financial asset over the period.

[22] Additional sources of complexity in the retail market for structured products are the type of underlying financial assets on which products are structured, and the complexity of marketing material/disclosures. While some of the products are indexed to unusual underlying financial indices, such as credit default swaps, the vast majority of the volumes are linked to local equity markets (almost 70%). Marketing material, such as prospectuses and marketing brochures, can amplify the perceived complexity of a product, but do not alter the actual complexity of calculating its payoff. Therefore, our measures of complexity can be interpreted as a lower bound of perceived complexity.

across languages, countries, financial institutions, and time, to provide clients with comparable information across products.[23]

Our main measure of the complexity of the payoff formula, *number of features*, is the number of features that compose the payoff formula, each feature adding one dimension to the contract.[24] We design this measure to apprehend the multidimensional contracts offered through retail structured products. The difficulty of understanding a product payoff formula and of comparing it with those of other products is indeed likely to increase with the number of dimensions of the payoff formula. For example, a *reverse convertible* feature, which exposes the investor to large underperformance of the underlying asset when this asset falls below a certain threshold, adds an *exposure modulation* dimension to the product. A second example of a frequently added feature is the *Asian option*, which indexes the value of the payoff to the average price of the underlying asset over a certain period of time, and which adds a *path dependence* dimension to the product. Tables A6 and A7 in the online appendix display the typology of features by dimension, and the definition of all features that a retail structured product payoff formula can possibly possess, which are grouped into eight dimensions.[25]

Our second measure of complexity, *number of scenarios*, is the number of possible scenarios that affect the final return formula. This measure is close 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.[26]

Our final and most parsimonious measure of complexity, *description length*, is the number of characters used in the text description of the payoff formula provided by the platform. This measure differs from the shear length of the prospectus, which is

[23]This consistent transposition of the payoff formula in plain English is a key feature of our dataset, which protects us against the bias arising from different languages and different methodologies among financial institutions that would arise from using prospectuses directly.

[24]We define as a dimension a group of features that are mutually exclusive.

[25]This approach relies on the assumption that all features defined in our typology are of comparable complexity. However, 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.

[26]This measure of complexity would overlook important dimensions, such as path dependence and underlying selection mechanisms.

not comparable across countries or distributors.

To extract these three measures of complexity, we calibrate and run for all 53,541 products a text analysis algorithm that scans the text description of the payoff formula. The algorithm searches for specific word combinations that correspond to each feature from our typology and counts them (*number of features*), identifies and counts conditional subordinating conjunctions, such as "if", "when", "in all other cases", "otherwise", and "whether" (*number of scenarios*), and counts the number of characters in the text description (*description length*). As per the headline rate, we manually check and improve the accuracy of our algorithm by iterating repeatedly on random subsamples.

Figure II shows how our methodology applies to two products: "Borsa Protteta Arancia" and "Fixeo", the latter being arguably more complex than the former. The former was distributed in 2009 by ING, and offers a headline rate of 4%, while the latter was distributed in 2010 by Credit Agricole, and offers a headline rate of 8%. Each product collected more than 50 million euros. Whereas the payoff formula of "Borsa Protteta Arancia" incorporates only one feature, a *digital*, the payoff formula of "Fixeo" includes three features, a *digital*, a *knock-out*, and a *reverse convertible.* "Fixeo", therefore, ranks higher in our main complexity measure, *number of features.* In addition, "Fixeo" is more complex according to the second and third complexity measures, as the payoff formula creates four distinct scenarios (compared to one scenario for "Borsa Protteta Arancia"), and its payoff description is significantly longer.[27]

3.3 Measuring Product Risk

As evidenced by the "6.2% Reverse Exchangeable Total" and "Fixeo" examples above, retail structured products frequently expose investors to a complete loss of their investments. Indeed, investors can lose up to their full initial investment with both products. Our measure of product risk is a dummy variable that identifies which

[27]See Table A2 in the online appendix for the complexity measures of the Top 3 "blockbuster"-structured products per country

Table II. Measuring Complexity

	Example 1: Borsa Protetta Arancia - Novembre 2009	**Example 2: Fixeo**
Details		
Year	2009	2010
Country	Italy	France
Provider	ING	Credit Agricole
Maturity	1	3
Description	This product is linked to the performance of the DJ Euro Stoxx 50. At maturity, [*if the underlying index registers a level equal to or higher than*] 70% of its strike level, [*the product offers a capital return of 104% of the initial investment*]$^{(1)}$. Otherwise, the product offers a capital return of 70% the initial investment.	This is a growth product linked to the DJ Eurostoxx50. After 1.5 years of investment, [*if*] the level of the index is at or above its initial level, then [*the product terminates*]$^{(1)}$ on that date and offers a capital return of 112% at that time. At maturity, the product [*offers a capital return of 124%, as long as*]$^{(2)}$ the final index level is at or above its initial level. [*Otherwise*] , the product offers a capital return of 100%, as long as the final index level is at or above 60% of its initial level. [*In all other cases*], the product offers a capital return of 100%, [*decreased by the fall in the index*]$^{(3)}$ over the investment period.
Headline Rate	4%	8%
Complexity Measures		
# Features	1	3
# Scenarios	2	4
Length	308	636
Payoff Features	(1) Digital	(1) Knockout (2) Digital (3) Reverse Convertible
Complete Loss Exposure	No	Yes

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

This table shows how our text-analysis algorithm collects from two actual product descriptions the product *headline rate*, three quantitative measures of complexity: *number of features*, *number of scenarios*, and *length.*, and the product risk, measured by a *complete loss exposure* indicator variable.

products expose investors to complete losses based on the features that our first text-analysis algorithm identifies.[28] The large majority of the products exposing investors to total losses include a reverse convertible feature in their payoff formula, which implies that, under certain conditions, the investor fully participates in the negative performance of the underlying financial asset. This measure focuses on losses coming from the payoff formula itself and hence, ignores the credit risk embedded in retail structured products that are not collateralized (Arnold et al. (2016)). Our risk measure is not based on the standard deviation or other moments of market prices, as most retail structured products are not traded on secondary markets.

3.4 Measuring Product Markup

Retail structured products yield profits to the banks that distribute them in addition to the disclosed fees. Indeed, the derivative structure embeds an undisclosed markup, as banks sell these products at a higher price than their fair value. We define the markup as the difference between a retail structured product issue price and the price at which the bank can hedge the position at issuance. We follow academic and industry practice for highly exotic products in using a local diffusion model in a Least Squares Monte Carlo setup to estimate the hedging cost.[29]

We apply this methodology to calculate the markups of 141 retail structured products with the Euro Stoxx 50 index as an underlying asset: the 102 issued in Europe in July 2009 and a random sample of 39 products issued in October 2010. Opting for a sample of products with the same underlying asset ensures that heterogeneity in both product complexity and markup derives only from the payoff formula and not the underlying financial asset. Furthermore, the choice of a single index as an underlying asset requires no assumptions regarding 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

[28] We crosscheck this variable with the information on minimum returns that the platform provides. These products indeed have a minimum final payoff equal to 0% of the initial investment.

[29] See the online appendix for more details on our pricing methodology.

products in our total sample. Euro Stoxx 50 options with various moneyness values and maturities trade daily on several exchanges with tight bid-ask spreads.[30] We price all products issued in July 2009 because the number of issuances and heterogeneity of products linked to Euro Stoxx 50 during that month is 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. We use high-quality, detailed volatility data from Eurex, the largest European derivative exchange.[31]

4 Basic Facts

This section provides summary statistics and basic facts about the main design characteristics of retail structured products: headline rates, payoff complexity, and risk.

4.1 Divergent Paths for Headline Rates and Interest Rates

Table III provides summary statistics of headline rates for the subsample of coupon products. The average headline rate is 8.2%, which is relatively high compared to the prevailing 5-year swap rate of 3.7% over the corresponding period. Figure III plots the evolution of the volume-weighted average of the spread between the average headline rate of retail structured products and the benchmark interest rate, and the benchmark interest rate itself over the 2002-2010 period in the Eurozone area.[32] Headline rates offered by retail structured products diverge significantly from the benchmark interest rate when interest rates are low.

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

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

[32] The benchmark interest rate is the 5-year swap rate, which is consistent with the average maturity of the products in our sample.

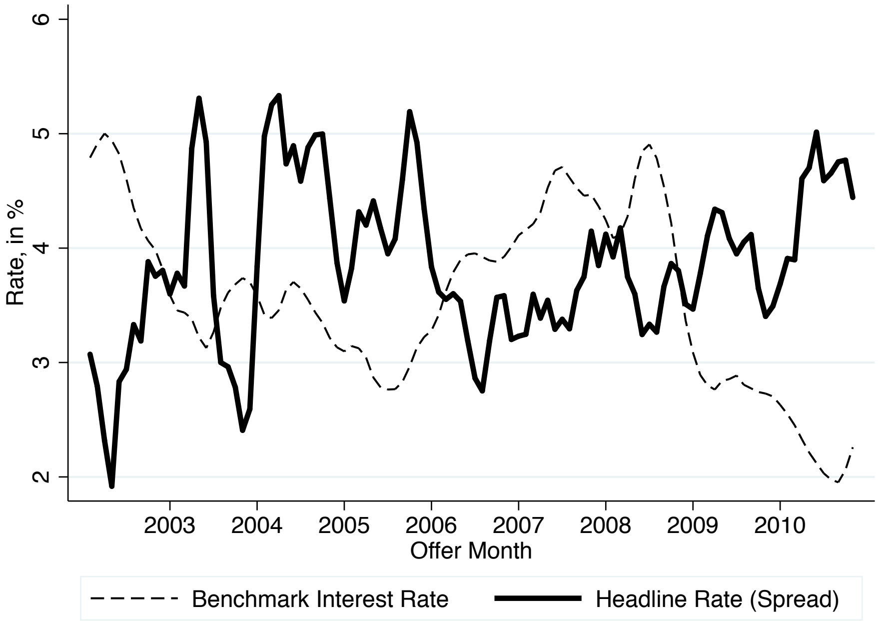

FIGURE III. Headline Rate and Benchmark Interest Rate

This figure shows the evolution of the average spread between the annual headline rate and the 5-year swap rate, weighted by volumes, and the 5-year swap rate in the Euro-zone Area. We exclude products issued in non-Eurozone countries. The headline rate is defined, for discrete payoff products, as the fixed rate that the investor receives in the best possible scenario and is obtained through a text analysis algorithm.

4.2 Increasing Complexity

The overall level of payoff complexity in the market is high. As Table III shows, the average product includes 2.5 features in its payoff formula and 2.2 scenarios, and requires 510 characters to describe its payoff. In addition, complexity is heterogeneous across products: the number of payoff features ranges from 1 to 7, the number of scenarios from 1 to 16, and the length of the payoff description from 140 to 2,124 characters. Among distribution channels, savings banks offer structured products with the highest level of complexity (see Table A10 in the online appendix for further statistics on the level of complexity by type of distributors).

Product complexity significantly increased over the 2002-2010 period, by more than 15%, with almost no decrease during the global financial crisis. Figure IV reports the coefficients of the year fixed effects when we run a volume-weighted regression

Table III. Summary Statistics

	Average	*Weighted Average*	**S. D.**	**Min**	**p25**	**p75**	**Max**	**N**
Headline Rate								
Yearly Coupon, in %	8.2	*7.4*	3.7	1.0	5.2	10.0	25.0	26,352
Spread to Benchmark, in %	4.6	*3.8*	3.7	-3.8	2.0	6.50	22.6	26,352
Complexity Measures								
# Features	2.5	*2.4*	1	1	2	3	7	53,541
# Scenarios	2.2	*2.1*	1.5	1	1	3	16	53,541
Length	510	*519*	207	140	361	630	2,124	53,541
Loss Exposure								
Indicator Variable	.29	*0.16*	-	-	-	-	-	53,541
Markup								
Product yearly markup, in %	.76	*0.90*	1.3	-1.8	0.1	1.3	12.5	141
Including disclosed fees	1.4	*2.0*	1.6	-1.4	0.3	1.9	12.5	141
Ex-post performance								
Product yearly return, in %	2	*2.2*	7.7	-81.0	0.0	4.7	125.3	5,841
Volumes								
In 2010 million Euros	21	-	67	0.0	4.4	19.0	3,106.6	46,613

This table displays summary statistics for the three measures of complexity developed in the study. *Number of features* is obtained through a text analysis of the detailed payoff description, *number of scenarios* by counting the number of conditions in the product description, and *length* by counting the number of characters of the payoff description. *Headline rate* is defined for coupon products as the fixed rate that the investor receives in the best possible scenario. *Complete Loss exposure* is an indicator variable equal to 1 if the investor is exposed to total losses. *Markup* is defined as the difference between issuance price and the fair value at issuance calculated using a local volatility diffusion.

of our complexity measures on a battery of product characteristics, such as type of underlying asset, distributor, format, country, and maturity. This large set of controls ensures that the increase in financial complexity is not driven by a mechanical compositional effect, such as a country or product type moving in or out of the market. The increase in complexity is qualitatively and quantitatively similar when we do not weight issuances by their volumes.[33] This increase in complexity is unlikely to result from regulatory changes. The text description we use, extracted from the

[33] Figure A4 in the appendix shows the non-conditional evolution of product complexity, the non-conditional evolution of product complexity weighted by volumes, and the conditional evolution of product complexity not weighted by volumes.

prospectus and translated by our data provider based on the same stable methodology over the years, is indeed not affected by changes in disclosure requirements, such as back testing and warnings.[34] Finally, Figure A5 in the online appendix plots the

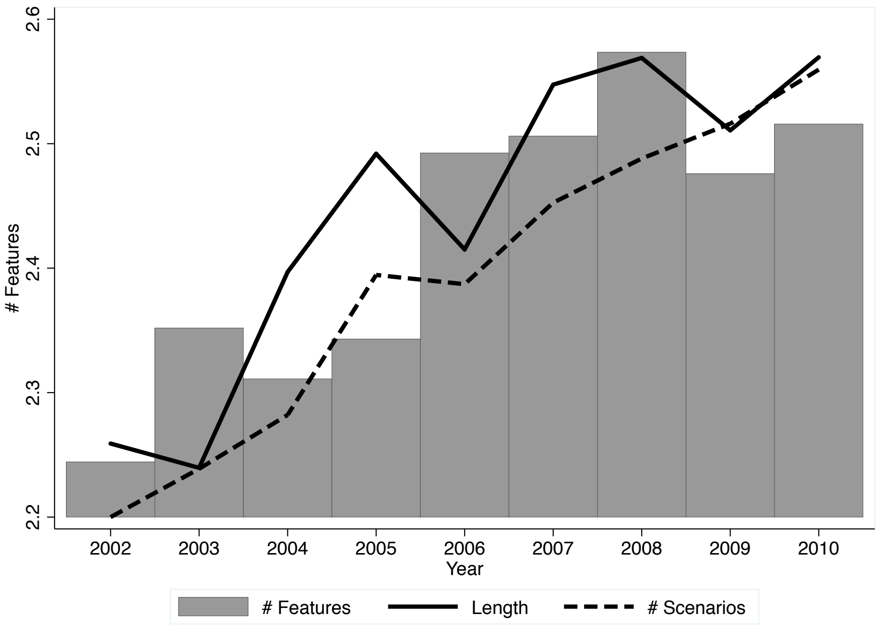

FIGURE IV. Evolution of Product Complexity

This figure shows the predicted complexity of retail structured products by year, calculated by estimating a volume-weighted OLS regression of product complexity over year fixed effects controlling for product and distributor characteristics. Complexity is measured as the number of features embedded in each product payoff formula, the number of scenarios, and the length of the payoff description in number of characters. The scale of the Y-axis, provided for purposes of clarity, refers only to the number of features. We obtain the complexity measures through a text analysis of the detailed text description of the payoff formula of retail structured products. The sample covers 53,541 products from 16 European countries.

distribution of issuance volumes along our complexity measures at the beginning and end of our sample. We observe that the increase in complexity results from changes within the whole distribution of complexity: the share of simple products decreases, while the share of more complex products increases. This evolution of

[34]We still consider the possibility that a change in regulation, specifically, implementation of the MiFID directive on November 1, 2007, might have produced a different methodology for describing payoffs, resulting in measurement error. Therefore, we control for the time consistency of text descriptions by manually identifying products with identical payoff features both before and after the implementation of the MiFID directive. During this audit exercise, we find that payoff descriptions remain similar and include approximately the same numbers of characters.

the complexity distribution is consistent with banks adding new features on existing payoff combinations, while progressively removing simpler products from the market.

4.3 Increasing Share of Risky Products

Figure V plots the share of volume of products exposing investors to complete losses, as defined in Section 3. The share of products exposing investors to complete losses

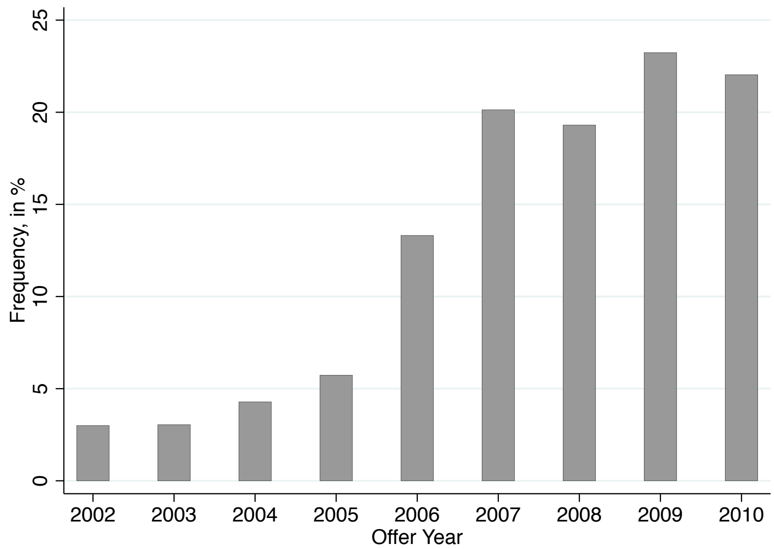

FIGURE V. Share of Volumes Exposing Investors to Total Losses
This figure displays the share of products issued over the 2002-2010 period that expose investors to complete losses.

significantly increased over our sample period, reaching 23% of volume in 2009. The evolution is qualitatively and quantitatively similar when we do not weight by volumes (see Figure A5 in the online appendix). This chart illustrates how structured product risk has been increasing in parallel with product complexity.

5 Determinants of Product Design

This section explores the cross-sectional determinants of product design. We explore how product headline rates, complexity, and risk relate to each other. In addition, this section investigates whether product design varies with the interest rate environment, characteristics of the financial institution distributing them, and whether it relates to product profitability.

5.1 Headline Rate and Product Complexity

We first investigate the relationship between headline rate and product complexity. Figure VI shows the volume-weighted average headline rate by level of complexity, as measured by our complexity measure, *number of features*. This figure suggests that the headline rate is an increasing function of complexity. We then regress the spread

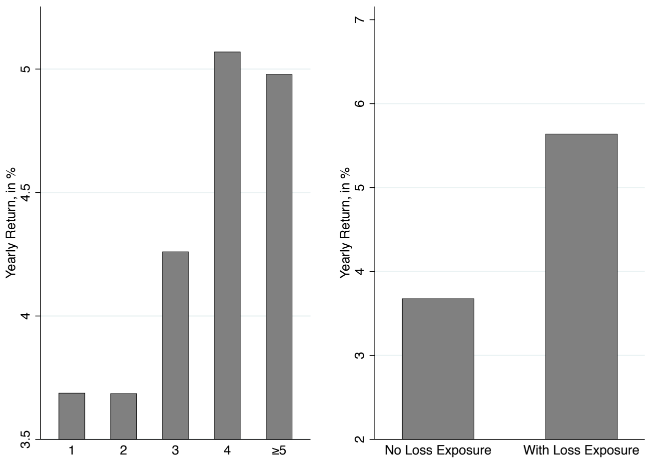

FIGURE VI. Headline Rate by Complexity Levels (Number of Features)
The figure shows the average spread between the headline rate and benchmark interest rate, weighted by volumes by level of complexity, as measured by our complexity measure, *number of features*, which is obtained through a text analysis of the detailed payoff description. *Headline rate* is defined for coupon products as the fixed yearly rate that the investor receives in the best possible scenario.

between the headline rate offered by our sample of 26,400 coupon products and the benchmark interest rate (the 5-year swap rate at issuance) on our three measures of product complexity, controlling for product characteristics.

$$Headline\ Rate_i = \alpha \times Complexity\ Measure_i + \beta X_i + \delta_y + \theta_c + \eta_d + \epsilon_i \qquad (1)$$

Complexity measure is alternatively *number of features*, *number of scenarios*, and *description length*, and X_i is a vector of product characteristics, which include the underlying asset class (equity, interest rates, exchange rates, commodities, or other), the format (certificate, structured note, deposit, fund, or life insurance), product maturity (in years), and volume sold. δ_y, θ_c, and η_d stand for year, country, and distributor fixed effects, respectively. Table IV presents the coefficients of these regressions. This multivariate regression analysis confirms our initial unconditional result. The headline rate is positively correlated with the level of product complexity, with both statistical and economic significance. Adding one additional payoff feature translates into 0.29% of additional yearly headline rate.[35] As expected, we also observe that the headline rate is higher for products exposing investors to complete losses (columns (7) and (8)), as higher risk allows to offer higher returns.

5.2 Product Complexity and Product Risk

We now explore whether product complexity relates to potential losses for the investor. Figure VII shows the share of issuance volumes that expose investors to complete losses by level of complexity.[36] More complex products more frequently expose the investor to complete losses.

We then run Logit regressions in which the dependent variable is a dummy equal to 1 if the payoff formula exposes the investor to complete losses. The explanatory variable is the level of product complexity, as measured by *number of features*, *number of scenarios*, and *description length.* To avoid any mechanical effect, we take the conservative approach of excluding the risky features from our measure of complexity, *number of features*, in this analysis, and accordingly adjust downward the number of scenarios. These Logit regressions include the same set of product characteristics as control variables as in equation (1), as well as year and distributor fixed effects. The results are displayed in Table V. The coefficients on our measures of complexity are positive and statistically significant, confirming that more complex products are more likely to expose investors to complete losses. For example, products with

[35] See Table A12 in the online appendix for the coefficients of the same regressions weighted by volumes.

[36] We use *number of features* as the measure of complexity.

Table IV. Headline Rate, Product Complexity and Risk

	Headline Rate (spread to benchmark), in %							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
# Features	0.504***	0.291***						
	(0.052)	(0.067)						
# Scenarios			0.434***	0.107**				
			(0.058)	(0.054)				
Length (1,000 characters)					1.849***	0.174		
					(0.606)	(0.304)		
Complete Loss Exposure							1.985***	0.932***
							(0.160)	(0.251)
Controls								
Distributor FE	-	Yes	-	Yes	-	Yes	-	Yes
Country FE	-	Yes	-	Yes	-	Yes	-	Yes
Underlying FE	-	Yes	-	Yes	-	Yes	-	Yes
Format FE	-	Yes	-	Yes	-	Yes	-	Yes
Maturity	-	Yes	-	Yes	-	Yes	-	Yes
Volume	-	Yes	-	Yes	-	Yes	-	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,352	26,352	26,352	26,352	26,352	26,352	26,352	26,352
R^2	0.033	0.219	0.046	0.215	0.025	0.214	0.077	0.221

This table displays the coefficients of OLS regressions in which the dependent variable is the spread between the product *headline rate* and the benchmark interest rate. *Headline rate* is defined for coupon products as the fixed yearly rate that the investor receives in the best possible scenario. The explanatory variables are the three complexity measures, as defined previously, and the measure of product risk, *Complete Loss Exposure*. 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.

one additional payoff feature have a 2.5% higher probability of having a risky feature embedded, controlling for year and distributor fixed effects as well as product characteristics.

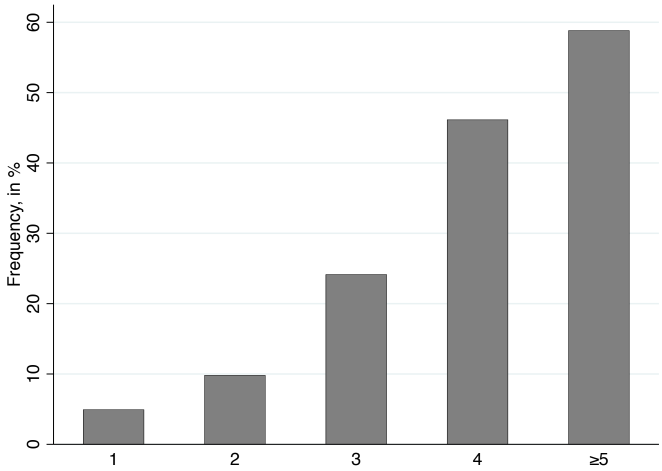

Figure VII. Share of Volumes Exposing Investors to Complete Losses by Complexity Levels (Number of Features)
The figure shows the share of product volumes exposing investors to complete losses by level of complexity, as measured by our complexity measure, *number of features*, which is obtained through a text analysis of the detailed payoff description. Products exposing investors to complete losses have a minimum final payoff of 0% of their initial investment.

5.3 Low-Interest Rate Environments

We now investigate how headline rates, product complexity, and product risk vary with the interest rate environment.

We use the heterogeneity in interest rates across countries from our sample to better identify the relationship between the level of headline rates offered by structured products on one side and the level of interest rates on the other, and whether interest rates are related to product complexity and risk. We use the seven different interest rates that correspond to the 16 countries in our sample: UK, Sweden, Norway, Denmark, Poland, Czech Republic, and Eurozone.[37] We estimate the following OLS model:

$$\textit{Headline Rate (spread)}_{i,c,t} = \alpha \times \textit{5y Swap Rate}_{c,t} + \beta X_i + \delta_t + \theta_c + \eta_d + \epsilon_{i,c,t} \quad (2)$$

where X_i is the usual vector of product characteristics, δ_t are year or quarter fixed

[37]Figure A8 in the online appendix displays the evolution of these interest rates over our sample period.

Table V. Complete Loss Exposure and Product Complexity

	Investor Exposed to Complete Losses (Indicator Variable) *Logit*					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
# Features	0.113*	0.181**				
	(0.067)	(0.087)				
# Scenarios			0.716***	0.759***		
			(0.050)	(0.068)		
Length (1,000 characters)					3.809***	5.876***
					(0.413)	(0.482)
Controls						
Distributor FE	-	Yes	-	Yes	-	Yes
Country FE	-	Yes	-	Yes	-	Yes
Underlying FE	-	Yes	-	Yes	-	Yes
Maturity	-	Yes	-	Yes	-	Yes
Volume	-	Yes	-	Yes	-	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	53,541	45,163	53,541	45,519	53,541	45,519
Pseudo R^2	0.040	0.377	0.165	0.438	0.129	0.464

This table displays the coefficients of logistic regressions in which the dependent variable is a dummy equal to 1 if the product exposes the investor to complete losses. To avoid any mechanical effect, we take the conservative approach of excluding the risky features from our measure of complexity, *number of features*, in this analysis, and accordingly adjust downward *number of scenarios*. 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.

effects depending on the specification, and θ_c and η_d represent country and distributor fixed effects, respectively. In a second step, we interact the level of interest rates with the spread between the country average interest rate prior to European monetary union and the European average.[38] This spread is a proxy for the household having been exposed to high-yield investments in the past.

Table VI displays the regression coefficients. In columns (1) and (2), we find a strong negative correlation between the spread of the headline rate with the bench-

[38]We use the swap rates from the 1992–1995 period, which precedes interest rate convergence within the Eurozone. The 1992–1995 average 5-year swap rate ranges from 6.8% in Germany to 11% in Italy. The European average over our sample is 8.6%. See Table A14 in the online appendix.

mark interest rate, and the level of the benchmark interest rate itself. The magnitude is large: a decrease of 1% in the benchmark interest rate corresponds to a deviation of 0.64% of the headline rate from this interest rate. Banks offset two-thirds of the decrease in interest rates in the headline rates.

In columns (3) to (5), we regress our three measures of product complexity on the benchmark interest rate. We find that periods of low interest rates are associated with higher product complexity, and again, that the relationship between complexity and interest rates is higher in countries that had high interest rates prior to the introduction of the euro.

Finally, in columns (6) and (7) of Table VI, we regress the indicator variable of products exposing the investor to complete losses on the benchmark interest rate. The coefficient of the interest rate is negative and significant for these specifications. Banks are more inclined to offer products exposing investors to complete losses in an environment with low interest rates. The coefficient of the interaction in column (7) is negative and significant: the relationship between interest rates and risk appears stronger in countries where interest rates were high before the introduction of the euro.

5.4 Bank Characteristics

We now explore whether product design varies with bank characteristics, including bank customer base and bank risk taking.

Table A10 in the online appendix presents statistics on the level of complexity per type of distributor: savings banks, commercial banks, and private banks. Savings banks, which target mainly rural and low- to middle-class households, distribute on average more complex products than the other types of distributors: commercial banks, private banks/wealth managers, and insurance companies. We confirm these unconditional statistics by regressing product complexity on distributor-type dummies while controlling for product characteristics. Table VII displays the regression coefficients. We find that savings banks distribute more complex products than commercial banks. The banks targeting the less sophisticated client base offer the most

Table VI. Headline Rate, Complexity and Risk in Low Interest Rate Environments

	Headline Rate		Product Complexity			Complete Loss Exposure	
	(Spread)		# Features	# Scenarios	Length	(Indicator)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Benchmark Rate	-0.641***	-0.670***	-0.133***	-0.065	-31.900***	-0.506***	-0.655***
	(0.182)	(0.211)	(0.043)	(0.047)	(9.395)	(0.181)	(0.188)
Benchmark Rate ×		-0.026	-0.040***	-0.045***	-6.313***		-0.144**
Historical Rates		(0.049)	(0.007)	(0.015)	(1.598)		(0.064)
Controls							
Distributor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Underlying FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Format FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maturity	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Volume	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,352	25,516	51,199	51,199	51,199	45,513	43,851
R^2	0.223	0.227	0.257	0.418	0.360	0.464	0.460

This table displays the coefficients of regressions in which the dependent variable is the spread between the product *headline rate* and the benchmark interest rate (5-year swap rate) in the first two columns, measures of *complexity* in columns (3) to (5), and an indicator variable for the product exposing the investor to potential complete losses, *complete loss exposure*, in columns (6) and (7). The explanatory variable is the 5-year swap rate, which takes different values in the Eurozone, the United Kingdom, Sweden, Norway, Denmark, Poland, and the Czech Republic. Historical Rates is the spread between the country average interest rate prior to European monetary union and the European average. Regressions include product controls and issuer, country, and year or quarter fixed effects. 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.

complex products.[39]

[39] Despite offering more complex products, savings banks do not offer products with significantly higher headline rate than other banks. This fact might result from larger markups by savings banks, which we observe in the data. Saving banks clients might face less attractive alternatives for investments than wealthier investors.

Table VII. Complexity Measures and Distributor Characteristics

	Headline Rate				# Features				Complete Loss Exposure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Bank Type												
Savings Bank	-0.171				0.240**				0.407			
	(0.291)				(0.120)				(0.371)			
Private Banking	0.305				0.202**				0.497*			
	(0.188)				(0.084)				(0.255)			
Bank Risk Taking												
Leverage Ratio		0.092**				0.042**				0.365***		
		(0.039)				(0.017)				(0.116)		
1 - Deposit Ratio			2.172***				0.923***				3.356***	
			(0.470)				(0.311)				(0.840)	
Greek Exposure				4.758***				1.302**				10.364***
				(1.201)				(0.521)				(3.062)
Controls												
Underlying FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maturity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Volume	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,352	15,582	15,183	10,692	53,541	31,340	30,500	21,270	53,541	31,340	30,500	21,270
R^2	0.117	0.114	0.125	0.141	0.093	0.119	0.121	0.113	0.167	0.239	0.220	0.282

The table displays the coefficients of OLS regressions in which the dependent variables are the three complexity measures and the explanatory variable is a dummy equal to 1 if the product distributor is a savings bank or a private banking institution (columns (1), (5) and (9)) - the control group consists of commercial banks-, and three proxies for bank risk taking: leverage, reliance on wholesale funding, and balance sheet exposure to Greek sovereign debt. Standard errors are clustered at the distributor level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% confidence levels, respectively.

We consider three proxies for bank risk taking: leverage, reliance on wholesale funding, and balance sheet exposure to Greek sovereign debt.[40]

Table VII shows how product complexity, headline rate, and exposure to complete

[40]Data are from Bankscope for leverage and wholesale funding, and from the 2011 European Banking Authority stress test for Greek sovereign exposure. Leverage ratio is calculated as the debt over total assets ratio, as at the end of 2002. We proxy reliance on wholesale funding by the 1 minus the ratio of deposits over total assets, as at the end of 2002. Greek sovereign exposure is calculated as the ratio of bank exposure to Greek sovereign debt over bank equity, as at the end of 2011.

losses all positively correlate with these three proxies for bank risk taking. These regressions control for bank size, as measured by log(total assets). In addition, banks that possess an investment banking division are more likely to offer products that expose investors to complete losses (see Tables A15 and A16 in the online appendix).

5.5 Product Profitability

A. Markups and Product Design

Finally, we empirically test the relationship between our main variables of interest and product markup.

Table III indicates that the average estimated yearly markup in our sample is 0.76%, or a 3.8% total markup for a 5-year product. Including disclosed entry and management fees, these amounts are 1.4% and 7%, respectively.[41,42] We regress product markups on headline rates on the indicator variable for product exposing investors to complete losses, and on the complexity measures, controlling for product characteristics. These controls include distributor fixed effects, as well as a dummy for non-collateralized products, such as bonds and deposits, because these products provide funding to the issuer, which affects profitability.[43]

Table VIII documents a statistically and economically significant relationship between markup at issuance and both the headline rate and complexity of the product. In addition, products exposing investors to complete losses appear more profitable.[44] The first column reports the result of regressing a product markup on its headline rate. We find that adding 1 standard deviation of headline rate corresponds to 21 basis points of additional yearly markup. Columns (2) to (4) present the coefficients

[41] Table A20 in the online appendix provides detailed information on each product we price and the corresponding undisclosed markup we calculate.

[42] 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 discount the flows for these products by the banks' funding cost. When we do so, we observe only two cases of negative markups.

[43] Arnold et al. (2016) analyze the pricing of credit risk in retail structured products.

[44] This result must be interpreted with caution, as it relies on the accurate pricing of reverse convertible features, which are designed with deeply out-of-the-money put options.

Table VIII. Headline Rates, Complexity, and Profitability

	Markup *Product Yearly Markup, in %*					**Ex-post Performance** *Product Yearly Return, in %*				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Headline Rate (spread)	0.056*					-0.051				
	(0.028)					(0.059)				
# Features		0.343***					-0.398***			
		(0.117)					(0.140)			
# Scenarios			0.196**					-0.626***		
			(0.082)					(0.212)		
Length (1,000 characters)				1.256**					-2.601**	
				(0.600)					(1.181)	
Complete Loss Exposure					0.782**					-3.496***
					(0.294)					(1.164)
Controls										
Loss Exposure FE	-	-	-	-	-	Yes	Yes	Yes	Yes	-
Distributor FE	Yes	Yes	Yes	Yes	Yes	-	-	-	-	-
Credit Risk	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Underlying FE	-	-	-	-	-	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Maturity FE	-	-	-	-	-	Yes	Yes	Yes	Yes	Yes
Observations	78	141	141	141	141	1,269	5,282	5,282	5,282	5,282
R^2	0.697	0.823	0.820	0.816	0.838	0.584	0.590	0.593	0.590	0.588

This table displays the coefficients of OLS regressions in which the dependent variable is the yearly markup in columns (1) to (5) and the ex post performance in columns (6) to (10). The explanatory variables are the spread between the *headline rate* and the benchmark interest rate in columns (1) and (6), an indicator variable for the product exposing the investor to potential total losses in columns (2) and (7), and the three complexity measures in columns (3) to (5) and (8) to (10). The sample for columns (1) to (5) consists of 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. This sample is restricted to coupon products in column (1). Markups are computed as the difference between the offer price and product 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 are from Eurex. The sample for columns (6) to (10) covers participation and digital products that matured before 2010. Control variables include a credit risk dummy indicating products that are non-collateralized. Standard errors are clustered at the distributor level and reported in brackets.

obtained when regressing markup on complexity measures. The coefficient on *#Features* is 0.34. Adding one additional feature in a payoff formula translates into an increase in the yearly markup of 0.34 percentage points and 1.7 percentage points of the total markup for a 5-year product. This amounts to an increase of more than 50% relative to the average markup. This relationship between profitability and complexity is robust to the complexity measure we use, as columns (3) and (4) show. Adding one additional scenario or 100 characters to the length of the description predicts increases of 0.2 and 0.13 percentage points, respectively, in the yearly markup. Finally, column (5) documents that products that expose investors to complete losses offer a significantly larger markup: 0.78 percentage points per year. In all these specifications, coefficients are of the same magnitude and significance in OLS regressions weighted by volumes (see Table A21 in the online appendix). However, when we regress the disclosed entry and management fees on the level of complexity, we do not obtain any significant relationship (see Table A22 in the online appendix).[45]

B. Ex-Post Performance and Product Design

We test whether product design explains *ex post* performance.[46]

Our database includes the final performance of 48% of the participation products that matured before 2011, which amounts to 7,500 products.[47] On average, the products in our sample earned a yearly return of 2%, which is 1.7 percentage points lower than the average risk-free rate for an equivalent maturity over the same period. In this subsample, 50% of the products offered an annual return of between 0% and 4.6%. We regress this *ex post* performance on the headline rate, the three complexity measures and the indicator variable equal to one if the product exposes the investor to complete losses. To ensure that our results are not driven by different levels

[45] This is consistent with some distributors marketing "zero-fee"-structured products, for which profitability accrues exclusively from the embedded markup.

[46] *Ex post* performance should be interpreted with caution, as it corresponds to one possible outcome.

[47] Because our data do 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. This prevents us from exploring a potential link between headline rate and *ex post* performance in a satisfying manner. *Ex post* performance is not available for Germany and Austria.

of risk associated with different levels of complexity, we also control for exposure to complete losses in our complexity regressions.[48] In column (6) of Table VIII, we observe no significant relationship between the headline rate and ex post performance, which suggests that the best scenario did not materialize frequently. Columns (7) to (9) present the estimated coefficients of the regression for our three measures of complexity. The three specifications indicate significant negative correlation between product complexity and performance. Adding one payoff feature reduces the yearly return by 0.58 percentage points. This result is both statistically and economically consistent with our previous finding in Section 5.5.A on markups. Finally, column (10) indicates that risky products underperformed, as some of the downside risk materialized.

6 Discussion

The main drivers of financial product design are still debated. Issuers may tailor securities to improve risk sharing (Allen and Gale, 1994; Duffie and Rahi, 1995), or alternatively, to increase opportunities for speculation (Simsek, 2013), screen for unsophisticated investors (Carlin, 2009), or extract agency rents (Biais et al., 2015; Biais and Landier, 2015).

This section compares our empirical results to the broad predictions of the two theories relevant to the retail market for structured products: (1) banks tailor securities to complete markets for households and improve risk sharing and (2) banks design their financial products to cater to unsophisticated investors' yield-seeking propensity while shrouding risk.

6.1 Theoretical Frameworks

Two simple theoretical frameworks may account for the security design we observe in the retail market for structured products. First, banks may tailor securities to share

[48]The design of retail structured products, especially capital protection, makes traditional approaches to adjust for risk, such as calculating excess returns, inappropriate.

risk better. In retail finance, banks may face households with heterogeneous levels of risk aversion, while having a narrow set of financial assets to offer. Banks may design products to offer different return and risk profiles, ranging from risk-free products with low expected returns to products with high risk and high expected return.[49] By adding a reverse convertible feature to the payoff formula of a product, for instance, banks can increase the risk of the product, and consequently its expected return. Some other payoff features, such as capital protection, reduce the risk of the product, and may allow risk-averse investors to invest in financial assets that would otherwise not be attractive to them.

Alternatively, banks may design their products to cater to yield-seeking investors and shroud risk. Retail investors may be prone to salient thinking and, consequently, may overweight headline rates, and neglect risk, when making investment decisions in low interest rate environments (Bordalo et al., 2012, 2016). Retail investors' salient thinking may encourage banks to offer products with high headline rates, in order to inflate investor's expectations.[50] One way for banks to increase the headline rate is to increase downside risk and to shroud it. The complexity of the payoff formula accomplishes this goal. In this framework, complexity is a by-product of banks catering the high yield appetite of households. Product complexity also increases the scope for banks to shroud markups (Gabaix and Laibson, 2006), thereby making it more likely that price (here, headline rate) becomes salient in equilibrium (Inderst and Obradovits, 2016).

6.2 Disentangling Theories

At first glance, several of our stylized facts on retail structured product design are consistent with both risk sharing and catering to the preferences of yield-seeking investors.

First, buying and selling options through a packaged product can be reconciled

[49] Symmetrically, banks may face assets with heterogeneous risk, as is arguably the case in the ABS market (see Furfine (2014)), and banks need to distribute this risk to potentially homogeneous investors, and rely on complex instruments to do so.

[50] High headline rates do not necessarily translate in high expected returns.

with both theories. Buying options typically reduces the risk of the underlying investment, while selling options increases its risk. In practice, it is difficult for retail investors to sell options directly, as doing so requires managing a margin account, and European regulators restrict these types of transactions. Hence, products that allow retail investors to sell options may help to complete markets. Conversely, products that implicitly sell options may be more attractive for yield-seeking investors, as they offer high headline rates. The investor receives the option premium in exchange for taking a risk.

The positive correlations between product headline rate and complexity, on one hand, and product complexity and exposure to complete losses, on the other hand, can also be reconciled with both theories. Tailoring the payoff function of retail structured products, thereby increasing its complexity, may allow banks to offer the risk exposure that matches investors' risk aversion. Adding one feature that implies a sale of a put option to a simple product, for instance, simultaneously increases the product complexity, headline rate, and risk.[51] Tailoring structured products to investors' heterogeneous levels of risk aversion is valuable, however, only under the assumption that retail investors cannot easily obtain comparable risk and return profiles by adjusting the risky share of their investment portfolio. Conversely, banks may increase the headline rate to attract salient-thinking investors, either by conditioning this rate on more criteria, or by shrouding risky features.

Third, the increasing complexity we observe, despite the absence of increase in household financial sophistication, could result from both technological improvements that allow banks to progressively better tailor the risk and return profiles of their products to household demand, and from reaching-for-yield. Banks may increasingly cater for yield-seeking investors through product complexity by offering high headline rates in a low interest rate environment.[52]

However, several of our results are difficult to reconcile with a risk-sharing ra-

[51] In addition, the sale of a put option increases the product expected return, as long as the option price implies risk aversion.

[52] In addition, the retail market for structured products may offer a channel through which banks could improve risk sharing by transferring specific risks to retail investors.

tionale for the complex design of retail structured products. Rather, these results are consistent with the main driver of product design being to cater for yield-seeking investors and shrouding risk.

First, banks offer products with relatively higher headline rate, and rely more on complexity, during periods of low interest rates. While the risk-sharing motive does not predict time variation in design according to the interest rate environment, this result is consistent with the main prediction of the salience framework: banks have a higher incentive to cater to yield-seeking investors when interest rates are low. In addition, this effect is stronger in countries where interest rates were high historically compared to the European average. This suggests that past experience could affect households' propensity to reach for yield, as has been documented for other types of financial decisions (Malmendier and Nagel (2016)).

Second, the share of risky products increases over our sample period. In the risk-sharing framework, under the assumption that retail investors are more risk averse than financial institutions, we should observe the opposite, as risk aversion has increased following the global financial crisis (Guiso et al. (2014)). However, this result is consistent with investors' salient thinking: investors are increasingly attentive to high headline rates in an environment of decreasing interest rates, at the detriment of product risk.

Third, we find that product markups are increasing with both headline rates and product complexity. This result is consistent with banks having more scope to capture large hidden markups in products offering higher headline rates, and more complex products. In addition, high headline rates do not predict higher *ex post* performance, and complex products underperform simpler ones, which is consistent with banks taking a larger markup on these products. The risk-sharing framework does not predict any systematic relationship between product design and profitability.

Fourth, the most complex products are offered by savings banks, the clients of which tend to be neither affluent nor investment savvy. It is unlikely that these households possess either the sophistication required to comprehend these products or the diversified portfolios that these complex products might optimally complement.

Conversely, clients from savings banks are more likely to be salient thinkers (Solomon et al. (2014); Stango and Zinman (2014)) as well as potentially more vulnerable to shrouding.

Finally, the creative marketing strategies for these products, which largely focus on the product headline rate, are supportive of a catering rationale.

7 Conclusion

We use unique data on a large market of investment products marketed to households and develop measures of headline rate, product complexity, and product risk. We establish that product complexity and the share of risky products increases in the 2002-2010 period.

We then explore the determinants of retail structured product design. We find, first, that products with higher headline rates are more complex and more frequently include a feature exposing the investor to complete losses. Second, both the spread between headline rates and interest rates and the complexity of products increase when interest rates are low. Finally, products with higher headline rates, more complex products, yield higher markups to banks. These *ex ante* higher markups translate into lower *ex post* performance for more complex products.

Our results support the view that banks design complex products to cater for yield-seeking investors. Our findings raise questions about the adequate regulation of complex instruments and investor protection in retail finance.

References

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

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

Anagol, S., S. Cole, and S. Sarkar (2015). Understanding the Advice of Commissions-Motivated Agents: Evidence from the Indian Life Insurance Market. *Harvard Business School Working Paper No. 12-055*.

Arnold, M., D. R. Schuette, and A. Wagner (2016). Pay Attention or Pay Extra: Evidence from Structured Product Counterparty Exposure. *Working Paper*.

Baker, M., R. Greenwood, and J. Wurgler (2009). Catering through Nominal Share Prices. *The Journal of Finance 64*(6), 2559–2590.

Baker, M. and J. Wurgler (2002). Market Timing and Capital Structure. *The Journal of Finance 57*(1), 1–32.

Becker, B. and V. Ivashina (2015). Reaching for Yield in the Bond Market. *Journal of Finance 70*(5), 1863–1902.

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

Bethel, J. E. and A. Ferrel (2007). Policy Issues Raised by Structured Products. *New Financial Institutions and Instruments: Opportunities and Policy Questions*, 167–193.

Biais, B. and A. Landier (2015). Endogenous Agency Problems and the Dynamics of Rents. *Working Paper, Toulouse School of Economics*.

Biais, B., J.-C. Rochet, and P. Woolley (2015). Dynamics of Innovation and Risk. *Review of Financial Studies 28*(5), 1353–1380.

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

Bordalo, P., N. Gennaioli, and A. Shleifer (2016). Competition for Attention. *Review of Economic Studies 83*(2), 481–513.

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

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

Duffie, D. and R. Rahi (1995). Financial Market Innovation and Security Design: An Introduction. *Journal of Economic Theory 65*(1), 1–42.

ESMA (2013). Retailisation in the EU. *ESMA Economic Report* (1).

Foerster, S., J. T. Linnainmaa, B. T. Melzer, and A. Previtero (Forthcoming). Retail Financial Advice: Does One Size Fit All? *Journal of Finance*.

Furfine, C. H. (2014). Complexity and Loan Performance: Evidence from the Securitization of Commercial Mortgages. *Review of Corporate Finance Studies 2*(2), 154–187.

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

Gennaioli, N., A. Shleifer, and R. Vishny (2015). Money doctors. *The Journal of Finance 70*(1), 91–114.

Ghent, A., W. Torous, and R. Valkanov (2016). Complexity in Structured Finance: Financial Wizardry or Smoke and Mirrors? *Working Paper*.

Greenwood, R., S. Hanson, and J. C. Stein (2010). A Gap-Filling Theory of Corporate Debt Maturity Choice. *The Journal of Finance 65*(3), 993–1028.

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

Guiso, L., P. Sapienza, and L. Zingales (2014). Time Varying Risk Aversion. *Working Paper*.

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

Hanson, S. G. and J. C. Stein (2015). Monetary policy and long-term real rates. *Journal of Financial Economics 115*(3), 429–448.

Harris, L. E., S. M. Hartzmark, and D. H. Solomon (2015). Juicing the dividend yield: Mutual funds and the demand for dividends. *Journal of Financial Economics 116*(3), 433 – 451.

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

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

Hoechle, D., S. Ruenzi, N. Schaub, and M. Schmid (2015). Financial Advice and Bank Profits. *Working Paper*.

Inderst, R. and M. Obradovits (2016). Excessive Competition for Headline Prices. *Working Paper*.

Inderst, R. and M. Ottaviani (2009). Misselling Through Agents. *The American Economic Review 99*(3), 883–908.

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

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

Kroszner, R. S. and R. G. Rajan (1994). Is the Glass-Steagall Act Justified? A Study of the US Experience with Universal Banking before 1933. *The American Economic Review 84*(4), 810–832.

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

Luo, M. (2016). Financial Product Design and Catering: Evidence from the Global Mutual Fund Industry. *Working Paper*.

Malmendier, U. and S. Nagel (2016). Learning from Inflation Experiences. *The Quarterly Journal of Economics* (131), 53–87.

Mullainathan, S., J. Schwartzstein, and A. Shleifer (2008). Coarse Thinking and Persuasion. *The Quarterly Journal of Economics 123*(2), 577–620.

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

Sato, Y. (2014). Opacity in Financial Markets. *Review of Financial Studies 27*, 3502–3546.

Schoar, A. and H. Ru (2016). Do Credit Card Companies Screen for Behavioral Biases? *NBER Working Paper Series w22360*.

Simsek, A. (2013). Speculation and Risk Sharing with New Financial Assets. *The Quarterly Journal of Economics 128*(3), 1365–1396.

Solomon, D. H., E. H. Soltes, and D. Sosyura (2014). Winners in the Spotlight: Media Coverage of Fund Holdings as a Driver of Flows. *Journal of Financial Economics 113*(1), 53–72.

Stango, V. and J. Zinman (2014). Limited and varying consumer attention evidence from shocks to the salience of bank limited and varying consumer attention: Evidence from shocks to the salience of bank overdraft fees. *Review of Financial Studies 27*(4), 990–1030.

Starr, A. (2015). Structured Products - Complexity and Disclosure - Do Retail Investors Really Understand What They Are Buying and What the Risks Are? *U.S. Security and Exchange Commission - Speech* (May 14).

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

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

Zaltman, G. (1997). Rethinking Market Research: Putting People Back in. *Journal of Marketing Research 34*(4), 424–437.