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Working Paper 16-050

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CATERING TO INVESTORS THROUGH PRODUCT COMPLEXITY *

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Abstract

This paper investigates the rationale for issuing complex securities to retail investors. We focus on a large market of investment products targeted exclusively at households: retail structured products in Europe. We hypothesize that banks strategically use product complexity to cater to yield-seeking households, by making product returns more salient and shrouding risk. We find four empirical results consistent with this view. First, we show that structured products with complex payoff formulas offer higher headline rates, and that they more frequently expose investors to a complete loss of their investment. We then document that banks are more inclined to issue high-headline-rate and more complex products in low-rate environments. Finally, we find that high-headline-rate and more complex products are more profitable for banks, and that their *ex post* performance is lower.

Keywords: Financial Complexity, Catering, Shrouding, Reaching for Yield, Household Finance, Structured Products

JEL codes: I22, G1, D18, D12

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1 Introduction

Since the end of the 1990s, European financial institutions have designed and sold more than 2 trillion euros of highly complex financial products to households: the so-called *retail structured products*. Built with derivatives, retail structured products include any investment products marketed to retail investors whose payoff is defined according to an *ex ante* formula over a given underlying financial index. These products have been broadly marketed in Europe, where access to such products is not limited to accredited investors, as it is in the US. For example, the product *Jayanne 4* was distributed by the French savings bank Credit Agricole in 2007, collected more than 2 billion euros, and has the following (arguably complex) payoff formula:

> *This is a growth product linked to a basket composed of the FTSE Euro First 80, the FTSE 100, the SMI and the NIKKEI 225. The Annual Performance is set at 5% for the first three years. In the following years, if the performance since the start date of the worst-performing index is positive or null, then the Annual Performance for that year is registered at 5%, otherwise 0%. The Basket Performance since the start date is registered every six months. The Final Basket Performance is calculated as the average of all these six-monthly readings, capped at a maximum basket performance of 100%. After 8 years, the product offers a guaranteed capital return of 100%, plus the greater of either the sum of the Annual Performances, or 100% of the Final Basket performance.*

The large product issuance illustrates how complex structured products have been successfully marketed to unsophisticated investors. Why do banks offer such complex securities to retail investors?

The motives for financial institutions to develop complex securities are still debated. Financial complexity is traditionally considered a corollary to financial innovation and is intended to improve risk sharing and better match investor demand (Allen and Gale, 1994; Duffie and Rahi, 1995). A growing theoretical literature, however, discusses a darker side of financial complexity. Banks may offer overly complex products to shroud some attributes or increase search costs (Gabaix and Laibson, 2006; Ellison, 2005; Carlin, 2009). They may also use complexity to offer high returns, thus catering to yield-seeking investors. Retail structured products represent an ideal laboratory to explore these motives because their flexibility in terms of payoff design allows banks to engineer payoff patterns that are potentially attractive to unsophisticated investors.

This paper introduces a novel dataset containing detailed information on all retail structured products sold in Europe between 2002 and 2010, totaling more than 1.3 trillion euros of issuance. The database covers approximately 55,000 products issued across 16 different countries by more than 400 distributors. The dataset also includes product characteristics, such as information on distributors and volume sold, and a detailed textual description of the payoff formula translated into English by the data provider, as in the Jayanne 4 example.

This dataset allows us to explore the interaction between retail structured product design and bank marketing strategies. The marketing of a retail structured product focuses primarily on making salient the payoff the investor receives in the best-case scenario, which we define as the *headline rate* in the remainder of the paper. The headline rate can be included in the name of the product or illustrated using persuasion techniques such as powerful images or key metaphors in the marketing brochure. We collect the headline rates of retail structured products using a text analysis algorithm that scans the textual payoff description of the products in our sample. We find that the average headline rate is 8.2%, which is relatively high compared with a benchmark interest rate of 3.7% over the corresponding period.[1]

This dataset also allows us to introduce three measures of product complexity. The first is intended to capture the multi-dimensionality of contracts offered in the retail market for structured products by counting the number of features that enter the payoff formula. The more dimensions a product has, the more difficult it is for

[1]We use the 5-year swap rate as the benchmark interest rate, as it broadly matches the maturity and credit risk of structured products.

a retail investor to understand and compare it with other products. Our second measure of complexity is the number of possible scenarios that affect the final payoff formula of the product. Finally, our third measure is the length, in the number of characters, of the text description of the payoff formula that is produced by the data provider. To compute these three measures of complexity, we calibrate and run a second text analysis algorithm. We establish that product complexity is high –the average product includes 2.5 features in its payoff formula, 2.2 scenarios, and requires 508 characters to describe its payoff– and increasing over our sample period.

Our empirical analysis relies on theoretical works on salience (Bordalo et al., 2012) and shrouding (Gabaix and Laibson, 2006). Bordalo et al. (2015) show that, in a low interest rate environment, banks can profitably cater to investors by issuing securities that offer a higher return at a moderately higher risk. Higher returns are indeed more salient to investors when alternative yields are low. This phenomenon is amplified when banks can shroud risk through product complexity. This framework yields four main predictions: products with higher headline rates should be more complex; products that expose investors to a complete loss of their investment should be more complex; products issued in low interest rate environments should offer relatively high headline rates and be more complex; and these high-headline-rate and more complex products should embed larger markups.

We provide evidence consistent with these four predictions. We first find that products offering high headline returns, and products exposing investors to market downturns, are more complex. One additional feature in the payoff formula of a retail structured product corresponds to 0.32% in additional yearly headline rate. This product is therefore 12% more likely to include a feature that exposes the investor to complete losses. Moreover, both the spread between headline rates and interest rates and product complexity increase when interest rates are low. Finally, we show that 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. These results are consistent with banks using product complexity to cater to retail investors.

Our work adds to several strands of the literature. First, our paper contributes to the literature on reaching for yield (Rajan, 2011; Yellen, 2011; Becker and Ivashina, 2015; Hanson and Stein, 2015) and issuers catering to investors (Baker et al., 2009; Baker and Wurgler, 2002; Greenwood et al., 2010).

Our work also adds to the literature on the role of financial literacy and limited cognition in consumer financial choice. Bucks and Pence (2008) and Bergstresser and Beshears (2010) explore the relationship between cognitive ability and mortgage choices. Lusardi et al. (2013), and Lusardi et al. (2010) document that household financial literacy is relatively low, and Lusardi and Tufano (2009) find lower financial literacy to be associated with poorer financial decisions. Financial product complexity might exacerbate the consequences of these problems.

The present paper also complements research on the dark side of financial advice provided to retail clients (Inderst and Ottaviani, 2009; Anagol et al., 2013; Bergstresser and Beshears, 2010; Hackethal et al., 2012; Karabulut, 2013; Hoechle et al., 2015; Foerster et al., 2015; Gennaioli et al., 2015) and of financial institutions' marketing strategies in retail finance. Schoar and Ru (2014) show that credit card companies exploit behavioral biases from 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., 2014; 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%.

Our paper proceeds as follows. Section 2 describes the data we use, explains the methodology for identifying headline rates and measuring complexity, and documents major trends in the retail market for structured products. In Section 3, we develop our hypotheses. In Section 4, we present our main results. Section 5 concludes.

2 The Retail Market for Structured Products

The retail market for structured products is an ideal laboratory to study how banks design and market complex financial instruments to cater to investors for three main reasons: (1) these products offer considerable flexibility to banks in terms of payoff design; (2) with assets under management of nearly one trillion dollars in Europe alone, this market is large; and (3) one can objectively measure the complexity of retail structured products.

2.1 Data and Product Characteristics

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

Retail structured products include any investment products marketed to retail investors 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 mainly based on equity indices and individual stocks but may also offer exposure to commodities, fixed income, or other alternative indices.

Our data source is a commercial data provider that has collected detailed information on all retail structured products sold in Europe since the inception of the market.[4] In addition to key information usually contained in prospectuses, such as issue date, maturity, underlying financial asset, and volume, the data source provides, for each product, a precise text description in English of the payoff formula.

Within the retail market for structured products, we focus on the largest cate-

[2]ETFs, 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]This firm provides the data to banks active in the structured products market. Cross-validation with practitioner documents and country-level comparisons with other academic studies suggest 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).

gory of products: tranche products. These products have a fixed maturity, are non-standardized, and are offered only during a limited period, typically 4 to 8 weeks. Tranche products represent 90% of the total volume of retail structured products.[5] Retail consumers investing in tranche products typically follow a buy-and-hold strategy owing to the significant penalties for exiting prior to maturity.

Our final dataset consists of detailed information on all 54,488 tranche retail structured products issued between 2002 and 2010 in 16 European countries. Cumulative volumes per country since the market's inception are reported in Table A4 of the online appendix. Italy, Spain, Germany, and France dominate in terms of volume sold, jointly constituting 60% of the total market. Figure I shows that issuance volume has been increasing at a rapid pace since market inception, with only a slight decrease after the financial crisis. We match the issuance-level data with additional information on providers (Bankscope and hand-collected data) and market conditions (Datastream) at the time of issue.

A retail structured product is defined along four main dimensions: the underlying financial asset, the payoff formula, the maturity and the 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: products rely on a single stock, a single index, a basket of shares, or a basket of indices. 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 a cap (see Table A3 in the online appendix for a definition of each of the payoff features). The maturity of a structured product is

[5] We therefore 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 such as warrants and turbos. Flow products, which include bonus and discount certificates, are highly popular 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.

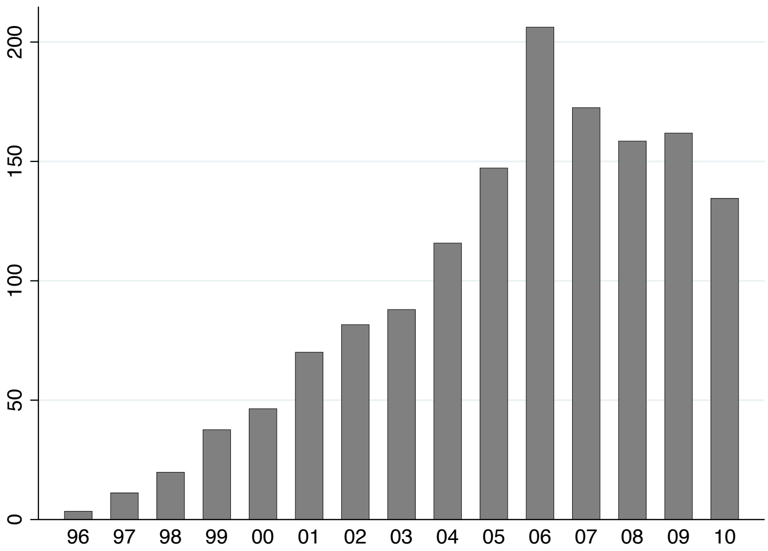

FIGURE I. Volume Sold per Year, in billions of euros
This figure shows, in billions of euros, volume issuance of tranche retail structured products in the European market over the 1996-2011 period. The countries include Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Ireland, Italy,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

4.2 years, on average, and ranges from less than one year up to more than 10 years. While retail structured products are designed by investment banks, they are mostly sold to households by commercial banks (66% of the volumes), with saving banks (16%) and private banks (15%) also having a significant share of the market.

2.2 Marketing of Retail Structured Products

A. Headline Rate

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 displays the payoff chart for this product.

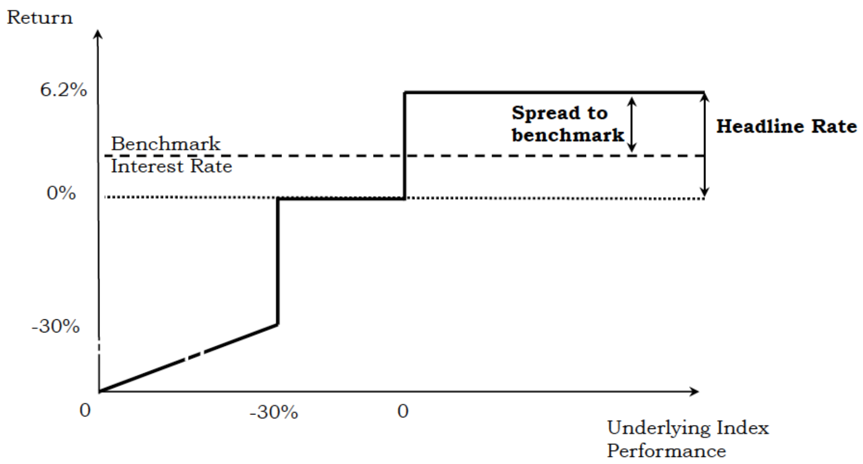

FIGURE II. Example of a Retail Structured Product Payoff
This diagram presents an example of a retail structured payoff and displays its related headline rate. The product offers a yearly coupon of 6.2% and a 100% capital return at maturity if the final performance of the underlying is positive (Eurostoxx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

We collect the headline rate of coupon products through a text analysis algorithm that scans the textual description of each pay formula.[6,7] This text description, produced by the data provider, translates into English the minimum information needed to calculate product performance.[8] 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 with the prevailing benchmark interest rate of 3.7% over the corresponding period.

[6]Coupon products pay a fixed amount each period, or at maturity, conditional on the performance of the underlying.

[7]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.

[8]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 A7 in the online appendix for product descriptions of the TOP 3 Blockbusters per country and corresponding headline rates.

B. Metaphors

Financial institutions appear to rely frequently on analogies and powerful metaphors in the marketing material of retail structured products, with the probable goal of making the headline rate more salient, facilitating the association of positive attributes with structured products by exploiting investors' "coarse thinking" (Mullainathan et al., 2008; Zaltman, 1997), and, conversely, downplaying the risk. Figure A1 in the online appendix provides two examples of the front page of retail structured product marketing brochures.

Product names, in France for instance, 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 positively assess 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.

2.3 Product Complexity

As evidenced by the *Jayanne 4* example in the introduction, retail structured products are often characterized by a complex payoff formula. This example, among others, calls for developing objective and robust measures of product complexity.

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 and Zaltman (2008). The sample covers all products issued in France from 2002 to 2010.

A. Measuring Product Complexity

This subsection develops three measures of the complexity of the payoff formula.[9] Our main measure of the complexity of the payoff formula, *Number of Features*, is

[9]We identify the payoff formula as the main source of heterogeneity in product complexity in this market. In our empirical analysis, we always control for other product characteristics that can potentially impact product complexity, such as the underlying financial asset or the format of the product.

the number of features that compose the payoff formula. This measure is intended to describe 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, increases with the number of dimensions.[10] Table A2 and A3 in the appendix displays the typology and the definition of all features that a retail structured product payoff formula can possibly possess, which are grouped into eight dimensions.[11]

Our second measure of complexity, *Number of Scenarios*, is the number of possible scenarios that affect the final return formula. 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.

Our final and most parsimonious measure of complexity, *Description Length*, is the number of characters used in the text description of the payoff formula.

To extract these three measures of complexity, we calibrate and run for all 54,488 products a second text analysis algorithm that scans the text description of the payoff formula.[12] 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*).

Figure II shows how our methodology applies to two products: Unigarant Euro Stoxx 50 2007 and Fixeo, the latter being arguably more complex than the former. Unigarant was distributed in 2002 by Volksbanken Raiffeisenbanken, whereas Fixeo was distributed in 2010 by the French savings bank Credit Agricole. Each product

[10]Studying only the non-linearity of the products means that the final payoff would overlook important dimensions such as path dependence and underlying selection mechanisms.

[11]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.

[12]This description, produced by our data provider, translates into English the minimum information needed to calculate product performance. This transposition has been made with consistency across countries, financial institutions and time.

collected more than 50 million euros. Whereas the payoff formula of Unigarant Euro Stoxx 50 incorporates only one feature, a *Call*, 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.* Fixeo is also more complex according to the second and the third complexity measures, as the payoff formula creates 4 distinct scenarios (against 1 scenario for Unigarant), and its payoff description is significantly longer.[13]

B. Evolution of Product 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, 2.2 scenarios and requires 508 characters to describe its payoff. Complexity also evidences strong heterogeneity across products: the number of payoff features ranges from 1 to 7, the number of scenarios from 1 to 6, and the length of the payoff description from 109 to 1,158 characters. Pairwise correlations of our complexity measures are in the [0.5 - 0.7] range, which suggests coherence and complementarity. Among distribution channels, savings banks are offering structured products with the highest level of complexity (see Table A6 in the appendix for further details 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 financial crisis. Figure III reports the coefficients of the year fixed effects when we regress the complexity measures on a battery of explanatory variables, such as type of underlying asset, distributor, format, country, volume, and maturity. 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 a market segment moving in or out of the market. Our result is also unlikely to result from regulatory change.[14]

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[13]See Table A7 in the online appendix for the complexity measures of the Top 3 "blockbuster" structured products per country

[14]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

Table II. Measuring Complexity

	Example 1: Unigarant: Euro Stoxx 50 2007	**Example 2: Fixeo**
Details		
Year	2002	2010
Country	Germany	France
Provider	Volksbanken Raiffeisenbanken	Credit Agricole
Maturity	5.5	3
Description	This is a growth product linked to the performance of the DJ Euro Stoxx 50. The product offers a [*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 the DJ Eurostoxx50. After one and a half 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.
Payoff Features	(1) Call	(1) Knockout - (2) Digital - (3) Reverse Convertible
Complexity Measures		
# Features	1	3
# Scenarios	1	4
Length	226	636
Headline Rate	n.a.	8%
Total Loss Exposure	No	Yes

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

This table shows how two actual product descriptions are converted into three quantitative measures of complexity: *Number of Features*, *Number of Scenarios* and *Length*.

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 of additional disclosures, such as back testing and warnings. Controlling for the time consistency of text

Table III. Summary Statistics

	Mean	S. D.	Min	p25	p75	Max	N
Complexity Measures							
# Features	2.5	1	1	2	3	7	54,488
# Scenarios	2.2	1.5	1	1	3	6	54,488
Length	508	212	109	356	633	1,158	54,488
Headline Rate							
Yearly Coupon, in %	8.2	3.7	1.0	5.2	10.0	25.0	26,388
Loss Exposure							
Indicator Variable	.29	-	-	-	-	-	54,488
Markup							
Product yearly markup, in %	.72	1.3	-1.8	0.0	1.2	12.5	157
Including disclosed fees	1.3	1.5	-1.4	0.3	1.8	12.5	157
Ex-post performance							
Product yearly return, in %	2.4	6.2	-58.6	0.0	4.6	66.5	8,982

This table displays summary statistics for the three measures of complexity developed in the paper. *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. *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 model (see section 4 for further details on the methodology).

2.4 Product Risk

As evidenced by the 6.2% Reverse Exchangeable Total and Fixeo examples, retail structured products frequently expose investors to a complete loss of their investment. With both products, investors can lose up to their initial investment.

Our data allows us to identify easily which products expose investors to complete losses: they have a minimum final payoff equal to 0% of the initial investment. We observe that these products represent 30% of the issuance products of our sample.[15]

descriptions by manually identifying products with identical payoff features both before and after the implementation of the MiFID directive, we find that payoff descriptions remain quite similar and include approximately the same numbers of characters.

[15] We ignore the potential credit risk embedded in retail structured products, and focus on losses coming from the payoff formula.

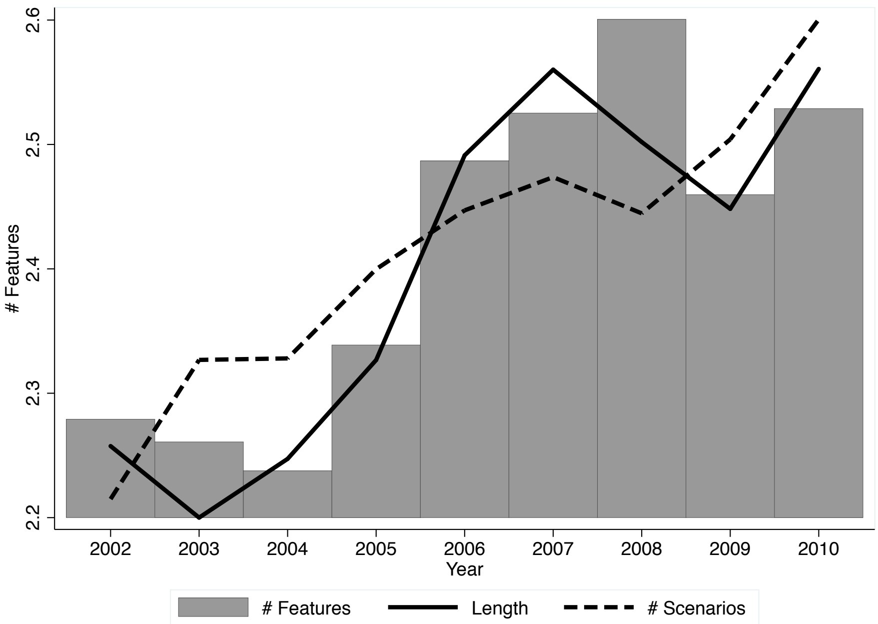

FIGURE III. Evolution of Product Complexity

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 and controlling for product and distributor characteristics. Complexity is measured as the number of features embedded in each product payoff formula, number of scenarios, and 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 54,488 products from 16 European countries.

The vast majority of these products 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. For example, with the product 6.2% Reverse Exchangeable Total, the investor fully participates in the negative performance of the underlying if its final level is below 70% of its initial level. This feature is frequently coupled with a worst of option (15% of the sample), implying that, when the underlying is a basket of share, the investor fully participates in the negative performance of the worst performing share.[16]

Figure IV shows that the share of the products exposing investors to complete

[16]More occasionally, the initial capital can be reduced by the outperformance of one share relative to another share of the same basket or, when the product performance is based on a credit event, the investor gets the value of the bond at maturity.

losses significantly increased over our sample period, reaching 35% of the issuances in 2010.

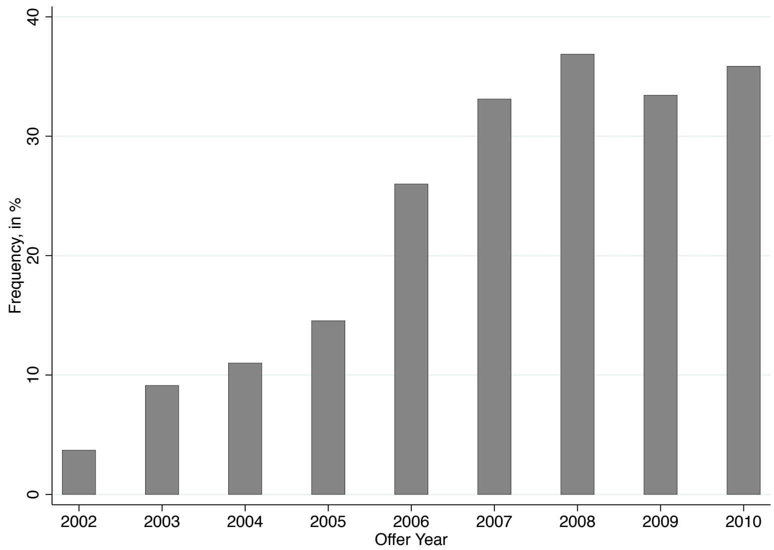

FIGURE IV. Ratio of Products Exposing Investors to Total Losses
This figure displays the share of products issued over the 2002-2010 period that expose investors to complete losses.

3 Hypotheses

The principal motive for financial institutions to develop innovative and complex securities is still debated. Issuers could tailor securities to improve risk sharing (Allen and Gale, 1994; Duffie and Rahi, 1995), conversely, to increase the opportunities for speculation (Simsek, 2013), or extract agency rents (Biais et al., 2015; Biais and Landier, 2015).

In retail finance, financial institutions could issue complex securities and shroud certain of their attributes to take advantage of unsophisticated retail investors (Ellison, 2005; Gabaix and Laibson, 2006; Carlin, 2009; Carlin and Manso, 2011). In addition, issuers may cater to investors by making certain attributes salient, such as headline rates (Bordalo et al., 2015). The retail market for structured products is well-suited to empirically investigate these theories because of the flexibility banks have in terms of payoff design. Banks would cater to investors by making some payoff attributes salient while shrouding others.

We derive four main hypotheses from this literature on strategic complexity and catering in retail finance.

First, Bordalo et al. (2015) predict that banks will aim at raising headline rates, to make their products more attractive, which generates the phenomenon of "reaching for yield". One way of doing so in the retail market for structured products is to add one or several features to a product's payoff formula, for instance by conditioning the headline rate on an intersection of events. The testable prediction is that products offering higher headline rates should be more complex.

Second, Gabaix and Laibson (2006)'s work suggests that banks will design complex financial products to shroud risk. It is indeed harder for a retail investor to assess a product's risk when its payoff formula is complex. Shrouding risk would amplify the "reaching for yield" phenomenon, by making returns relatively more salient. This framework predicts that products embedding risky attributes for the investor should be more complex.

Third, banks should have a stronger incentive to increase the headline rate - relative to the benchmark interest rate - when interest rates are low, as investors' propensity to reach for yield is higher in these environments. Because increasing the complexity of payoffs allows improving the headline rate, banks should rely more on complexity, and embed more frequently risky features, during periods of low interest rates. Consequently, headline rates should diverge more from the benchmark interest rate during these periods.

Finally, both shrouding and salience theories predict that banks should capture larger profits when they design complex securities. This should translate into complex products having larger markups than simpler ones.

4 Results

This section empirically tests the four hypotheses and finds supportive evidence.

4.1 Catering to Reaching-for-Yield Investors

We first test whether more complex products offer higher headline rates. Figure V shows the 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.

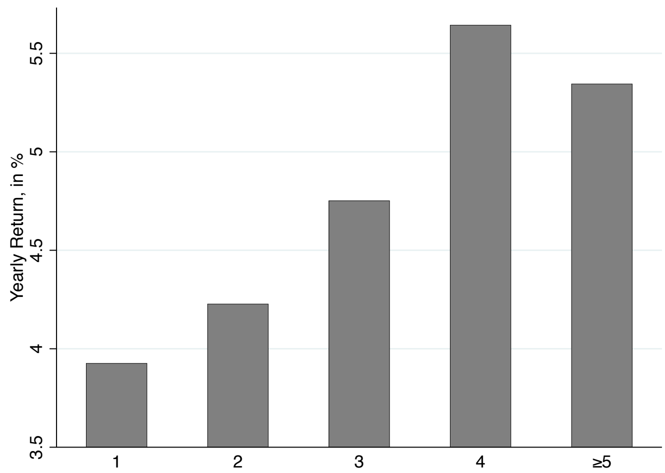

FIGURE V. Headline Rate by Complexity Levels (Number of Features)
The figure shows the spread between the average headline rate and the benchmark interest rate by level of complexity, as measured by our complexity measure *Number of Features*, which is obtained through a text analysis of the detailed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

We then estimate the following OLS model where we regress the headline rate offered by our sample of 26,400 coupon products on our three measures of product complexity.

$$\textit{Headline Rate}_i = \alpha \times \textit{Complexity Measure}_i + \beta X_i + \delta_y + \theta_c + \eta_d + \epsilon_i \qquad (1)$$

where *Complexity Measure* is alternatively *Number of Features*, *Number of Scenarios* and *Description Length*, 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 respectively stand for year, country and distributor fixed effects.

Table IV presents the coefficients of these regressions. The headline rate is positively correlated with the level of product complexity, with both statistical and economic significance. For instance, adding one additional payoff feature translates into 0.31% of additional yearly headline rate.

Table IV. Catering to Reaching-for-Yield Investors: Headline Rate and Product Complexity

	Headline Rate (spread to benchmark), in %					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
# Features	0.469***	0.313***				
	(0.060)	(0.068)				
# Scenarios			0.384***	0.110*		
			(0.063)	(0.058)		
Length (1,000 characters)					1.628**	0.022
					(0.644)	(0.336)
Controls						
Distributor FE	-	Yes	-	Yes	-	Yes
Country FE	-	Yes	-	Yes	-	Yes
Underlying FE	-	Yes	-	Yes	-	Yes
Format FE	-	Yes	-	Yes	-	Yes
Maturity	-	Yes	-	Yes	-	Yes
Volume	-	Yes	-	Yes	-	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,388	25,639	26,388	25,639	26,388	25,639
R^2	0.052	0.245	0.061	0.241	0.045	0.241

This table displays the coefficients of OLS regressions in which the dependent variable is *Headline 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. 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.

This result is consistent with banks using complexity as a way to increase headline rates, thus catering to yield-seeking investors.

4.2 Risk Shrouding

We explore whether complexity is associated with large potential loss for the investor.

Figure V shows the share of products which expose investors to complete losses by level of complexity, as measured by *Number of Features*. More complex products more frequently expose the investor to complete losses.

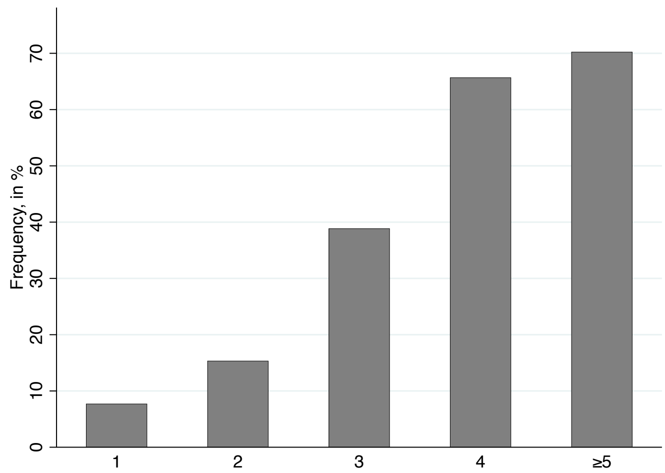

FIGURE VI. Share of Products Exposing Investors to Complete Losses by Complexity Levels (Number of Features)
The figure shows the share of products exposing investors to complete losses by level of complexity, as measured by our complexity measure *Number of Features*, which is obtained through a text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

We then conduct Logit regressions where the dependent variable is a dummy equal to one if the payoff formula expose 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 subtracting one feature and one scenario from our measures *Number of Features* and *Number of Scenarios* when the left hand side variable is equal to one. 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.

Results are displayed in of Table V. The coefficients on our measures of complexity are all positive and statistically significant, confirming that more complex products are more likely to expose investors to complete losses. For example, products with one additional payoff features have a 12% higher probability to embed a risky feature, after controlling for year and distributor fixed effects as well as product characteristics.

This result is consistent with banks using complexity to shroud risk.

Table V. Risk Shrouding: Loss Exposure and Product Complexity

	Investor Exposed to Complete Losses (Indicator Variable) *Logit*					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
# Features	0.117**	0.175**				
	(0.057)	(0.074)				
# Scenarios			0.715***	0.650***		
			(0.052)	(0.062)		
Length (1,000 characters)					3.534***	4.488***
					(0.390)	(0.784)
Controls						
Distributor FE	-	Yes	-	Yes	-	Yes
Country FE	-	Yes	-	Yes	-	Yes
Underlying FE	-	Yes	-	Yes	-	Yes
Format FE	-	Yes	-	Yes	-	Yes
Maturity	-	Yes	-	Yes	-	Yes
Volume	-	Yes	-	Yes	-	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	54,488	45,340	54,488	45,340	54,488	45,340
Pseudo R^2	0.042	0.474	0.166	0.517	0.125	0.527

This table displays the coefficients of logistic regressions in which the dependent variable is a dummy equal to one if the product exposes the investor to potential total losses. For the purpose of this analysis, *Number of Features* and *Number of Scenarios* do not include the features that create the risk. 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.

4.3 Favorable Environments

We now investigate whether headline rates, product complexity, and product risk increase in environments in which investors are more prone to reaching for yield and more vulnerable to risk shrouding.

A. Low Interest Rate Environments

Figure VII plots the evolution 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 Euro-zone Area. [17] The figure illustrates how the average level of the headline rate diverges more from the benchmark interest rate when interest rates are low. This empirical fact is consistent with an amplified reaching-for-yield phenomenon during period of low interest rates.

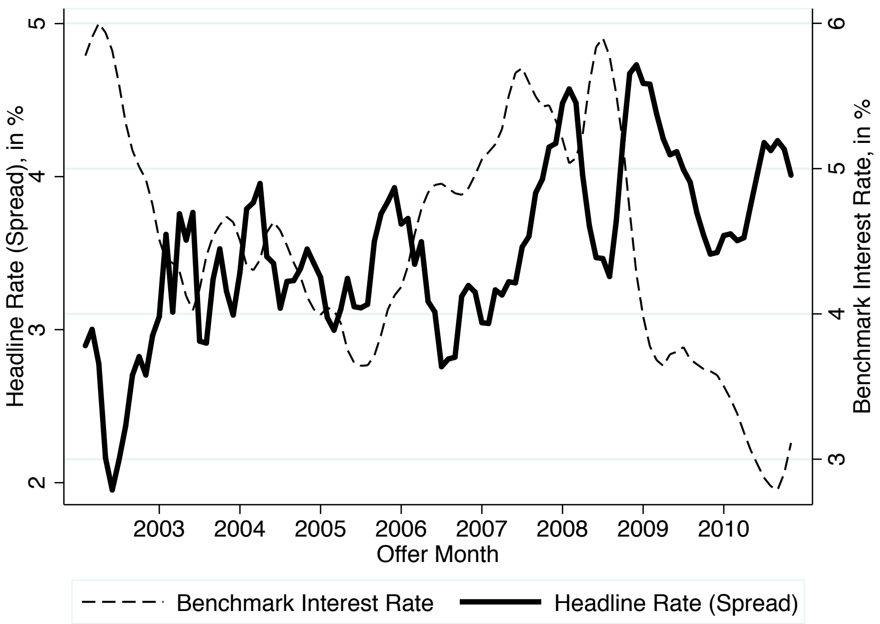

FIGURE VII. Headline Rate and Benchmark Interest Rate
This figure shows the evolution of the average spread between the annual headline rate and the 5-year swap rate, and the 5-year swap rate in the Euro-zone Area. We therefore exclude products issued in non-Euro-zone countries. The headline rate is 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.

We then use the heterogeneity in interest rates across countries from our sample to better identify the negative relationship between the level of headline rates offered

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

by structured products on one side and the level of interest rates on the other. We use the seven different interest rates that correspond to the 16 countries we cover in our sample: the British, Swedish, Norwegian, Danish, Polish, Czech and Euro Area interest rates.[18]. We estimate the following OLS model:

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

where X_i is the usual vector of product characteristics, δ_t are year or quarter fixed effects depending on the specification, and θ_c and η_d respectively stand for country and distributor fixed effects.

Columns (1) and (2) of Table VI display the regression coefficients. We find a strong negative correlation between the spread of the headline rate with the benchmark 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 0.7% of the headline rate from this rate.

In columns (3) and (4) of Table VI, we also regress the indicator variable equal to one if the product exposes the investor to complete losses and the three complexity measures, on the benchmark interest rate. The coefficient of the interest rate is again negative and significant for all these specifications. Hence, banks are more inclined to offer products exposing investors to complete losses in an environment with low interest rates.

In columns (5) to (7), we regress product complexity on the benchmark interest rate. We find that periods of low interest rates are associated with higher product complexity.

Taken together, these three findings are consistent with banks using complexity to cater to yield-seeking retail investors in low rate environments.

[18]Figure A3 in the online appendix displays the evolution of these interest rates over our sample period.

Table VI. Reaching for Yield and Risk Shrouding in Low Interest Rate Environments

	Headline Rate (Spread)		Loss Exposure (Indicator)		Product Complexity		
					# Features	# Scenarios	Length
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Benchmark Rate	-0.872***	-0.703***	-0.522***	-0.480***	-0.095**	-0.029	-29.453***
	(0.135)	(0.186)	(0.091)	(0.158)	(0.044)	(0.036)	(9.097)
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
Year FE	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	25,639	25,639	45,334	45,334	52,697	52,697	52,697
R^2	0.218	0.223	-	-	0.250	0.415	0.358
$PseudoR^2$	-	-	0.474	0.477	-	-	-

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 (5Y Swap Rate) in the first two columns, an indicator variable for the product exposing the investor to potential complete losses, *Loss Exposure*, in columns 3 and 4, and measures of *Complexity* in columns 5 to 7. The explanatory variable is the 5-year swap rate, which takes different values in the Euro Area, the UK, Sweden, Norway, Denmark, Poland and the Czech Republik. 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.

B. Bank Customer Base

We now investigate the level of complexity of products offered by savings banks, which target mainly rural and low- to middle-class households. This background makes savings bank customers more likely to be salient thinkers (Solomon et al. (2014), Stango and Zinman (2014)), as well as potentially more sensitive to shrouding.

We regress product complexity on an indicator variable that is equal to one if the product is marketed by a savings bank. Table VII displays the regression coefficients. We find that savings banks distribute more complex products than our control group, which comprises commercial banks.[19] This result is difficult to reconcile with the view that the most complex products are targeted at the most sophisticated segment of the market. However, this result is consistent with savings banks relying more on complexity because their customer base is reaching for yield and/or vulnerable to shrouding.

Table VII. Complexity Measures and Distributor Customer Base

	# **Features**	# **Scenarios**	**Length**
	(1)	**(2)**	**(3)**
Savings Bank	0.147**	0.459***	39.673**
	(0.070)	(0.128)	(17.978)
Controls			
Underlying FE	Yes	Yes	Yes
Maturity	Yes	Yes	Yes
Volume	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	52,703	52,703	52,703
R^2	0.085	0.148	0.117

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 one if the product distributor is a savings bank. The control group consists of commercial banks. The type of bank is from Bankscope or hand collected. Standard errors are clustered at the distributor-year level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% confidence levels, respectively.

[19]See Table A6 in the online appendix for unconditional statistics.

4.4 Headline Rates, Complexity and Profitability

A. Complex Products Markups

We empirically test the prediction that products offering a higher headline rate, products that expose investors to complete losses, and more complex products, embed a larger markup. We define 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.

For this purpose, 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, $\frac{dS_t}{S_t} = r_t dt + \sigma\left(t; S_t\right) dW_t$, 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.[20,21] 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)) that is 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.[22]

[20]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.

[21]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.

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

We apply this methodology to calculate the markups of 148 retail structured products with the Euro Stoxx 50 index as an underlying: the 101 issued in Europe in July 2009 and a random sample of 47 products issued in October 2010. Opting for a sample of products with the same underlying 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 requires no assumption regarding implied correlation between stocks, as opposed to products linked to a basket of stocks. Moreover, 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.[23] We choose to 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.

In terms of market data, we obtain high-quality, detailed volatility data from Eurex, the largest European derivative exchange.[24] Table III indicates that the average estimated yearly markup in our sample is 0.72%, or a 3.6% total markup for a five-year product. Including disclosed entry and management fees, these amounts are 1.3% and 6.5%, respectively.[25,26]

We regress product markups on headline rates, on the indicator variable for product exposing investors to complete losses, and on the complexity measures, controlling

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

[24] Although we use the highest quality implied volatility data available, we cannot account for volatility in 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.

[25] Table A10 in the online appendix provides detailed information on each product we price and the corresponding undisclosed markup we calculate.

[26] 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.

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 impacts profitability.[27]

Table VIII documents a statistically and economically significant relationship between markup at issuance and both the headline rate and the complexity of the product. Products exposing investors to complete losses also appear to be more profitable.[28]

The first column reports the result of regressing a product markup on its headline rate. We find that adding one standard deviation of headline rate corresponds to 21 basis points of additional yearly markup. This result is consistent with banks capturing a share of investors' inflated expectations in terms of the likelihood of the headline rate. Column (2) suggests that products that expose investor to complete losses offer a significantly larger markup: 0.78 percentage points per year. Columns (3) to (5) present the coefficients obtained when regressing markup on complexity measures. The coefficient on *#Features* is 0.33. Adding one additional feature in a payoff formula translates into an increase in the yearly markup of 0.33 percentage points, 1.65 percentage points of the total markup for a five-year product. This amounts to a more than 50% increase relative to the average markup. This relationship between profitability and complexity is robust to the complexity measure we use, as columns (4) and (5) show. Adding one additional scenario or 100 characters to the length of the description predicts increases of 0.20 and 0.12 percentage points, respectively, in the yearly markup. However, when we regress the disclosed entry and management fees on the level of complexity, we do not obtain any significant relationship (see Table A9 in the online appendix).[29] We also conduct several robustness checks on the asset pricing methodology in the online appendix (Table A9).

These results are consistent with our theoretical prediction.

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

[28]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.

[29]This is consistent with some distributors marketing "zero fees" structured products, for which profitability comes exclusively from the embedded markup.

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	0.057*					-0.063				
	(0.028)					(0.059)				
Loss Exp.		0.782**					-3.203**			
		(0.294)					(1.267)			
# Features			0.325***					-0.581**		
			(0.107)					(0.226)		
# Scenarios				0.196**					-0.886***	
				(0.082)					(0.238)	
Length					1.235**					-2.920***
					(0.604)					(1.090)
Controls										
Distri. FE	Yes	Yes	Yes	Yes	Yes	-	-	-	-	-
Credit Risk	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Underl. 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
Observations	78	141	141	141	141	1,281	5,636	5,636	5,636	5,636
R^2	0.698	0.838	0.821	0.820	0.816	0.592	0.588	0.582	0.587	0.557

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 headline rate in column 1 and 6, an indicator variable for the product exposing the investor to potential total losses in column 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 the 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.

B. Ex-Post Performance of Complex Products

We also test whether more complex products exhibit lower *ex post* performance. *Ex post* performance should be interpreted with caution, as it corresponds to one possible outcome. However it represents an interesting validity test with a larger sample for the result on profitability. Our database includes the final performance of 48% of the participation products that matured before 2011, which amounts to some 7,500 products.[30] On average, the products in our sample earned 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. 50% of the products in this subsample offered an annual return comprised between 0% and 4.6%.

We regress this *ex post* performance on the headline rate, on the indicator variable equal to one if the product exposes the investor to complete losses, and on the three complexity measures. 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*, which indicates whether the initial capital invested is guaranteed at maturity.[31]

Columns (8) to (10) in Table VIII present the estimated coefficients of the regression for our three measures of complexity. The three specifications indicate a 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 on markup.

5 Conclusion

We use unique data on a large market of investment products marketed to households to test the hypothesis that banks issue complex financial products to cater to yield-

[30]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.

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

seeking investors while shrouding risk.

We find the design and returns of retail structured products to be largely consistent with this hypothesis.

We first document that more complex products offer a higher headline rate than simpler products 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. Additionally, savings banks, which target low- to middle-income households, offer products that are on average more complex. Finally, we show that more complex products and products with higher headline rates yield higher markups to banks. These *ex ante* higher markups translate into lower *ex post* performance for more complex products.

Our findings raise questions concerning the regulation of complex instruments and investor protection in retail finance.

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