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Working Paper

Catering to investors through product complexity

ESRB Working Paper Series, No. 14

Provided in Cooperation with:

European Systemic Risk Board (ESRB), European System of Financial Supervision

Suggested Citation: Célérier, Claire; Vallée, Boris (2016) : Catering to investors through product complexity, ESRB Working Paper Series, No. 14, ISBN 978-92-95081-41-3, European Systemic Risk Board (ESRB), European System of Financial Supervision, Frankfurt a. M., <https://doi.org/10.2849/9466>

This Version is available at:

<https://hdl.handle.net/10419/193521>

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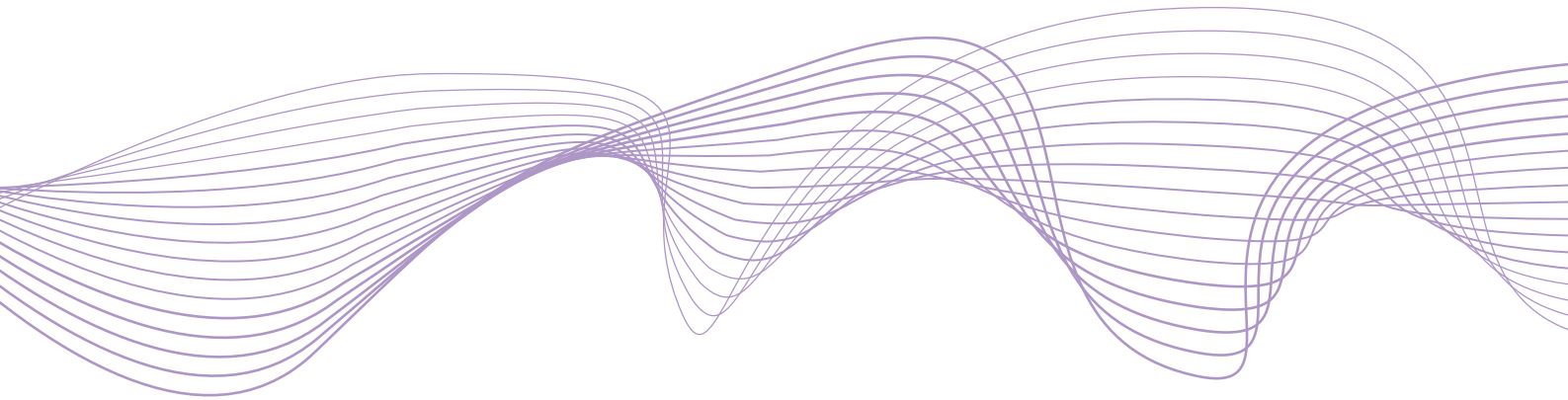
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Working Paper Series

No 14 / June 2016

Catering to investors through
product complexity

by
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ESRB

European Systemic Risk Board

European System of Financial Supervision

Abstract

This study 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 develop an economic measure of product complexity in this market via a text analysis of 55,000 product payoff formulas. Over the 2002–2010 period, product complexity increases, risky products become more common, and product headline rates diverge from the prevailing interest rates as the latter decline. The complexity of a product is positively correlated with its headline rate and risk. Complex products appear more profitable to the banks distributing them, have a lower ex-post performance, and are more frequently sold by banks targeting low-income households. These empirical facts are consistent with banks strategically using product complexity to cater to yield-seeking households.

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

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, so-called *retail structured products*. 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, which use derivatives, have been marketed broadly 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.

When maturing in 2015, *Jayanne 4* paid off 116% of the original investment, which corresponds to a 1.8% annualized return.¹

The motives for financial institutions to sell complex securities to households are still debated. Financial complexity is traditionally considered a corollary to financial innovation and is intended to improve risk sharing and to match investor demand

¹This performance implies that the *Final Basket Performance* ended up one percent higher than the lower possible level of the sum of the *Annual Performances*.

better (Allen and Gale, 1994; Duffie and Rahi, 1995). A growing number of theoretical studies, however, discuss the 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). In addition, banks may use complexity to offer high returns, thereby catering to yield-seeking investors. Retail structured products represent an ideal laboratory to explore these motives. The flexibility of these products in terms of payoff design allows banks to engineer payoff patterns that make them attractive to unsophisticated investors.

This study introduces a novel dataset containing detailed information on all *core* retail structured products sold in Europe between 2002 and 2010, totaling more than 1.3 trillion euros of issuance. *Core* products represent 90% of the total volume of retail structured products. The database covers approximately 55,000 products issued across 16 different countries by more than 400 distributors. In addition, the dataset includes product characteristics, such as information on distributors and volumes sold, and, most importantly, 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 develop measures of product complexity, headline rate, and risk through an algorithmic text analysis of the product payoff descriptions. Our first measure of product complexity 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 a retail investor to understand and compare the product 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. We define the *headline rate* as the yearly return the investor receives in the best-case scenario. The marketing strategy of retail structured products largely focuses on this headline rate, for instance, by including it in the name of the product or by relating it to marketing metaphors. Finally, we measure product risk with an indicator variable on whether the product exposes investors to a complete

loss.

Armed with these measures of product complexity, headline rate, and risk, we document three basic facts about the retail market for structured products. First, product complexity increases significantly from 2002 to 2010, with no discernible drop during the global financial crisis. Second, headline rates diverge from the level of interest rates when interest rates are low. Third, the fraction of products exposing investors to complete losses increases significantly over our sample period.

We then explore the determinants of product complexity. We first find that products offering high headline rates and products exposing investors to complete losses are more complex. Second, the spread between product headline rates and interest rates increases when interest rates are low, as do 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 low-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 drivers of financial complexity. First, complexity aims to improve risk sharing (Allen and Gale, 1994; Duffie and Rahi, 1995). Second, banks cater to yield-seeking investors through complexity and shrouding (Bordalo et al., 2012; 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, the higher headline rates and complexity when interest rates are low and the higher profitability of complex products are only consistent with the catering rationale for developing these products. Our empirical results are also consistent with 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) and issuers catering to investors (Baker and Wurgler, 2002; Baker et al., 2009; Greenwood et al., 2010).

Second, 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 is associated with poorer financial decisions. Financial product complexity might exacerbate the consequences of these problems.

Third, the present study 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 bias 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) show theoretically 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 complexity, headline rates, product risk, and markups. Section 4 documents basic facts in the retail market for structured

products and Section 5 explores the determinants of product complexity. Section 6 discusses our empirical findings in light of two theories. 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 subsequently, has experienced steady growth. In 2012, with 770 billion euros of assets under management, the retail market for structured products stands 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 global volumes. The US and Asian markets, however, have been growing fast: retail structured product assets under management exceed 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 over our sample period. Specific rules to regulate the distribution of these products are rare: while Italy

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

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

⁴Source: ESMA (2013).

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

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}

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 cases suggests that these disclosure requirements may not be sufficient at reducing information asymmetry between distributors and retail investors.⁹ The 2007 MiFID, on the other hand, 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. In addition, this directive 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 directive.^{10,11}

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

⁷In 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/96621.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.fsm.a.be/en/Doormat/Consultations/Cons/Article/press/div/2011-08-12_consult.aspx).

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

⁹The 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.

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

¹¹Measuring the exact effect of the application of the first MiFID directive on the retail market for

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 represent 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 A10 in the Appendix).

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2.2 Original Dataset

Our analysis is based on a unique 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).¹³ 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.¹⁴ 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

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.

¹²Bethel and Ferrel (2007) details the US legal framework for retail structured products prior to the Dodd–Frank Wall Street Reform and Consumer Protection Act.

¹³Corporate clients of the platform include, among others, JP Morgan, Barclays, Credit Suisse, and Commerzbank.

¹⁴Some distributors ask the platform to disclose certain information, such as issuance volumes, only at an aggregate level.

of issuances and volumes, 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 our 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 4 to 8 weeks. *Core* products represent 90% of the total volume of retail structured products as per the data collected by our provider.¹⁵ Retail investors investing in these products typically follow a buy-and-hold strategy owing to the significant penalties for exiting prior to maturity.¹⁶ Information on volume sold is available at the issuance level for more than 60% of total volumes, 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.¹⁷

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 measure product complexity, 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 intermediary cash flows. The coverage for this information is not exhaustive: it is available for 46% of the products that have matured and have no intermediary cash

¹⁵Therefore, 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.

¹⁶The 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.

¹⁷The average is computed after excluding products with disclosed volumes.

flows in our sample. The dataset we obtain initially includes 68,433 issuances of core products from the 18 European countries.¹⁸ Each issuance is identified uniquely by its ISIN code, as required by European regulation. 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). Therefore, 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 cumulated issuance.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 Main Product 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: 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

¹⁸These 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.

¹⁹This compares with samples covering 1,588 products, one country, and 50 billion US dollars of issuance in Henderson and Pearson (2011).

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 volumes), 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 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 issuance volumes have been increasing at a rapid pace since market inception, with only a slight decrease after the global financial crisis.

2.4 Product Marketing

Financial institutions appear to rely frequently on analogies and powerful metaphors in the marketing material of retail structured products. Hence, financial institutions may exploit investors' "coarse thinking" to facilitate the association of positive attributes with structured products while downplaying the risk ((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. The diversity and creativity of product names perfectly 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

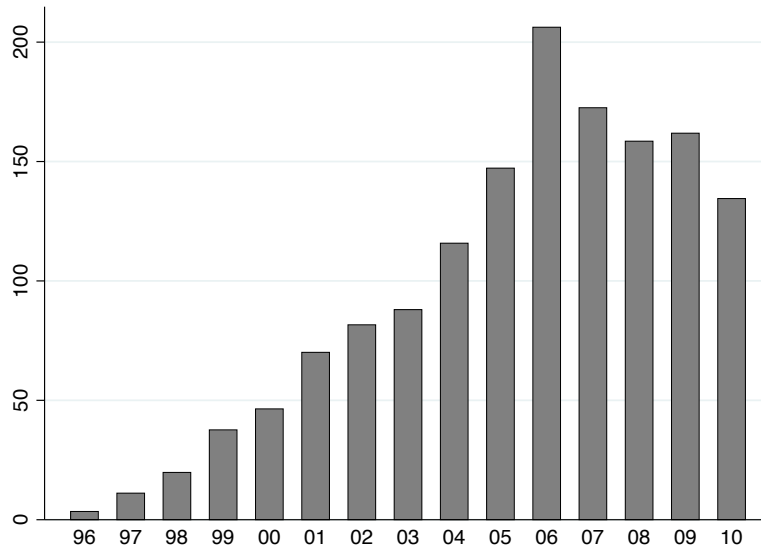


FIGURE I. Volumes Sold per Year

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.

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.

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

3.1 Measuring Payoff Complexity

We develop three measures of the complexity of the payoff formula. As the *Jayanne* 4 example in the introduction illustrates, the payoff formula is the main source of product complexity in this market.²⁰

²⁰Additional 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 ma-

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

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

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.

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

terial/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.

maturity. The platform transposes retail structured product prospectuses consistently across languages, countries, financial institutions, and time, to provide clients with comparable information across products.²¹

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.²² 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.²³

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.²⁴

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

²¹This 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.

²²We define as a dimension a group of features that are mutually exclusive.

²³This 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.

²⁴This measure of complexity would overlook important dimensions, such as path dependence and underlying selection mechanisms.

the platform. This measure differs from the shear length of the prospectus, which is 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*). Pairwise correlations of our complexity measures are in the [0.5–0.7] range, which suggests coherence and complementarity.

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 Credit Agricole. Each product 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*. 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 Unigarant), and its payoff description is significantly longer.²⁵

3.2 Measuring the Headline Rate

As illustrated by the Fixeo example in Table II, retail structured products tend to offer high returns in their best possible scenario. We define this annualized return as the product headline rate. Figure II displays the net payoff diagram of a product marketed by Commerzbank in 2009 in Germany, Austria, Spain, the Netherlands, and Belgium. The product includes a digital payoff with a reverse convertible feature,

²⁵See Table A2 in the online appendix for the complexity measures of the Top 3 “blockbuster”-structured products per country, which include Jayanne 4

Table II. Measuring Complexity

	Example 1: Unigarant: Euro Stoxx 50 2007	Example 2: Fixeo
<i>Details</i>		
Year	2002	2010
Country	Germany	France
Provider	Volksbanken Raiffeisenbanken	Credit Agricole
Maturity	5.5	3
<i>Description</i>		
	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 rate of 50% in the rise of the underlying] ⁽¹⁾ over the investment period	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.
<i>Payoff Features</i>		
	(1) Call	(1) Knockout - (2) Digital - (3) Reverse Convertible
<i>Complexity Measures</i>		
# Features	1	3
# Scenarios	1	4
Length	226	636
<i>Headline Rate</i>		
	n.a.	8%
<i>Total Loss Exposure</i>		
	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*.

which offers a yearly coupon of 6.2% and a 100% capital return at maturity if the final performance of the underlying asset is positive, but 100% participation in the negative performance of the underlying asset if its final level is below 70% of its initial level.

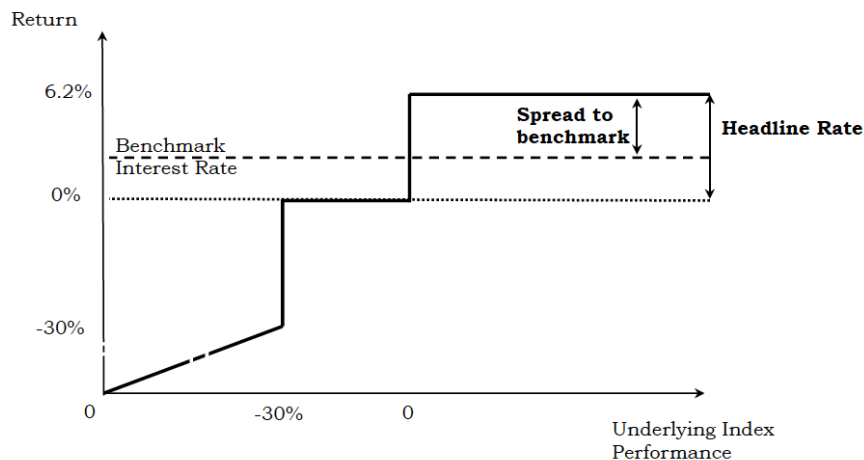


FIGURE II. Example of a Retail Structured Product Payoff

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.

The marketing schemes of retail structured products typically highlight this headline rate. In the previous example, the headline rate of 6.2% is included in the product name, *6.2% Reverse Exchangeable Total*. We collect the headline rate of *coupon* retail structured products through a second text analysis algorithm that scans the textual description of each payoff formula.^{26,27} 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.

3.3 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 in-

²⁶Coupon products pay a fixed amount each period, or at maturity, conditional on the performance of the underlying asset.

²⁷For 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.

vestments. 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 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.

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, $\frac{dS_t}{S_t} = r_t dt + \sigma(t; S_t) dW_t$, where S_t is the price of the underlying asset, $\sigma(t; S_t)$ 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 price complex structured products accurately because they frequently have deeply embedded out-of-the-money options, such as an implicit sale of put options or cap

²⁸We 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.

on the final payoff.^{29,30} Retail structured product payoffs are largely path dependent. To account for this specificity, we use the Least Squares Monte Carlo methodology (Longstaff and Schwartz (2001)), which is widely recognized and implemented by academics and professionals alike. This approach uses ordinary least squares to estimate the conditional expected payoff to the option holder from continuation, which affords a better estimation of the optimal exercise of a American option when its value depends on multiple factors.³¹

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 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 values and maturities trade daily on several exchanges with tight bid-ask spreads.³² 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. We

²⁹Henderson 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.

³⁰Models 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.

³¹We appreciate the support of the LexiFi pricing tool to perform this calculation-intensive methodology accurately, which includes both local volatility diffusion and Least Squares Monte Carlo. Deutsche Bank, HSBC, Societe Generale, and Bloomberg are among the many financial institutions and their service providers that use this tool to price structured products. See www.lexifi.com for details.

³²Although 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.

use high-quality, detailed volatility data from Eurex, the largest European derivative exchange.³³

4 Basic Facts

This section provides summary statistics and basic facts about our main variables of interest: product complexity, headline rate, and product risk.

4.1 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 shows evidence of strong heterogeneity 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 A8 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 III reports the coefficients of the year fixed effects when we run a volume-weighted regression 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 market segment 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.³⁴ This increase in complexity is unlikely to

³³Although 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.

³⁴Figure 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

Table III. Summary Statistics

	Average	Weighted Average	S. D.	Min	p25	p75	Max	N
<i>Complexity Measures</i>								
# Features	2.5	2.5	1	1	2	3	7	53,541
# Scenarios	2.2	2.1	1.5	1	1	3	16	53,541
Length	510	513	207	140	361	630	2,124	53,541
<i>Headline Rate</i>								
Yearly Coupon, in %	8.2	7.7	3.7	1.0	5.2	10.0	25.0	26,352
<i>Loss Exposure</i>								
Indicator Variable	.29	0.19	-	-	-	-	-	53,541
<i>Markup</i>								
Product yearly markup, in %	.76	0.93	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
<i>Ex-post performance</i>								
Product yearly return, in %	2	2.0	7.7	-81.0	0.0	4.7	125.3	5,841
<i>Volumes</i>								
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. *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.

result from regulatory changes. The text description we use, being extracted from the 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.³⁵ Finally, Figure IV plots the distribution of issuance volumes along our complexity measures at the beginning and end of our sample.

product complexity not weighted by volumes.

³⁵We 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.

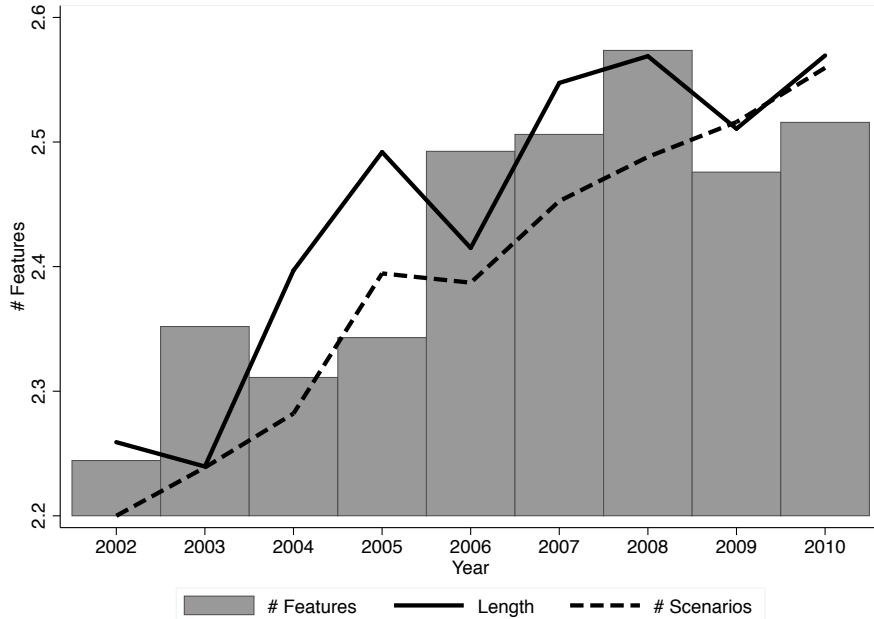


FIGURE III. Evolution of Product Complexity

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.

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

4.2 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 with the prevailing 5-year swap rate of 3.7% over the corresponding period. Figure V

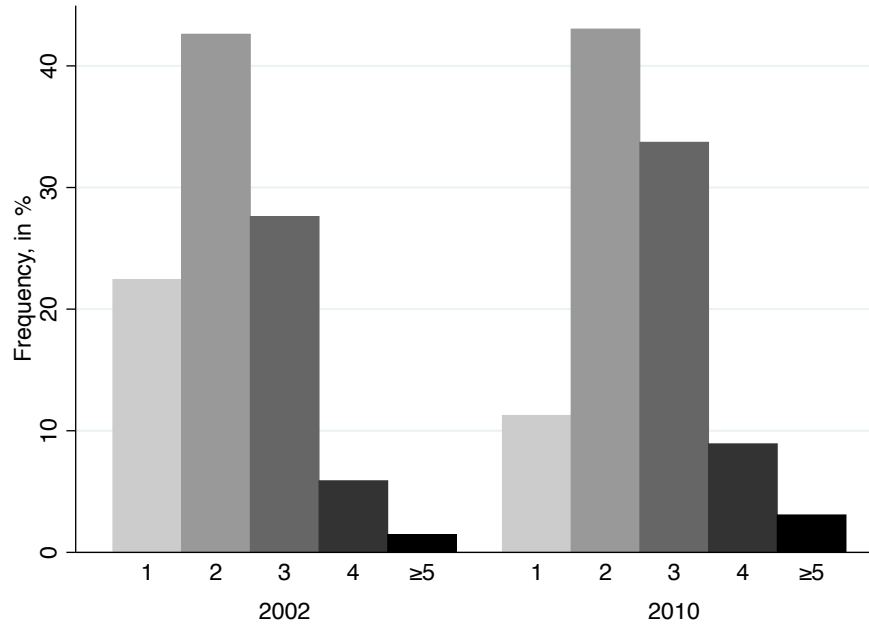


FIGURE IV. Evolution of the Distribution of Product Complexity

This figure shows the share of product volumes by level of complexity, as measured by *number of features*, in 2002 and 2010.

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.³⁶ Headline rates offered by retail structured products diverge significantly from the benchmark interest rate when interest rates are low.

4.3 Increasing Share of Risky Products

Figure VI 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 significantly increased over our sample period, reaching 23% of volumes 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.

³⁶The benchmark interest rate is the 5-year swap rate, which is consistent with the average maturity of the products in our sample.

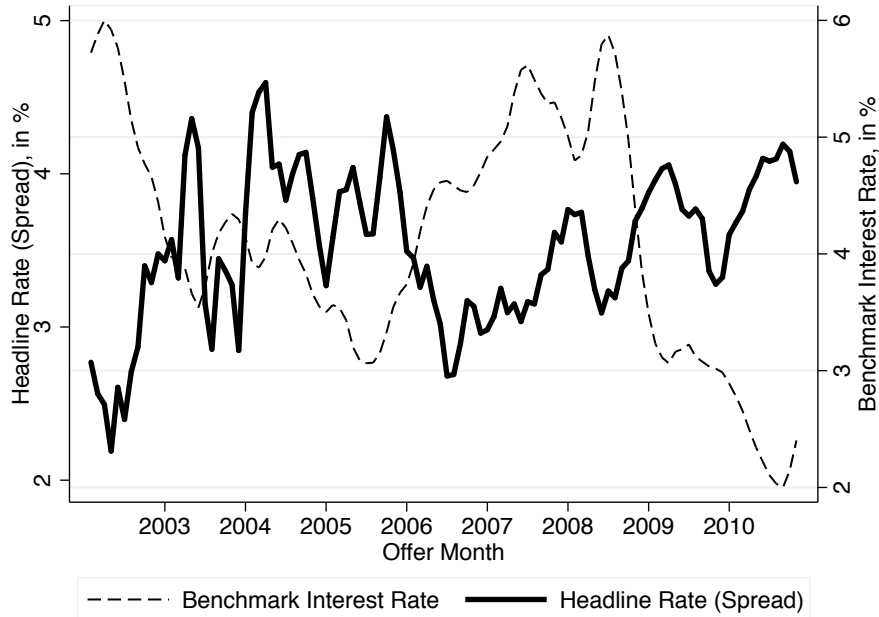


FIGURE V. Headline Rate and Benchmark Interest Rate

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. Therefore, 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.

5 Determinants of Product Complexity

This section explores the cross-sectional determinants of product complexity. We test whether products offering higher headline rates and riskier products are more complex. In addition, this section investigates whether product headline rate, product risk, and financial complexity vary with the interest rate environment, characteristics of the financial institution distributing them, and product profitability.

5.1 Product Complexity and Headline Rate

We first investigate the relationship between product complexity and headline rate. Figure VII shows the volume-weighted average headline rate by level of complexity, as measured by our complexity measure, *number of features*. This figure suggests that

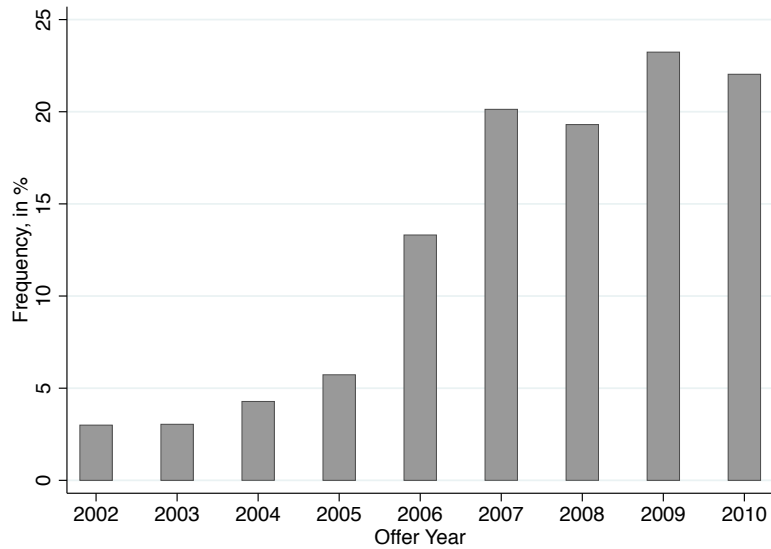


FIGURE VI. Share of Volumes Exposing Investors to Total Losses

This figure displays the share of products issued over the 2002–2010 period that expose investors to complete losses.

the headline rate is an increasing function of complexity. We then regress the spread

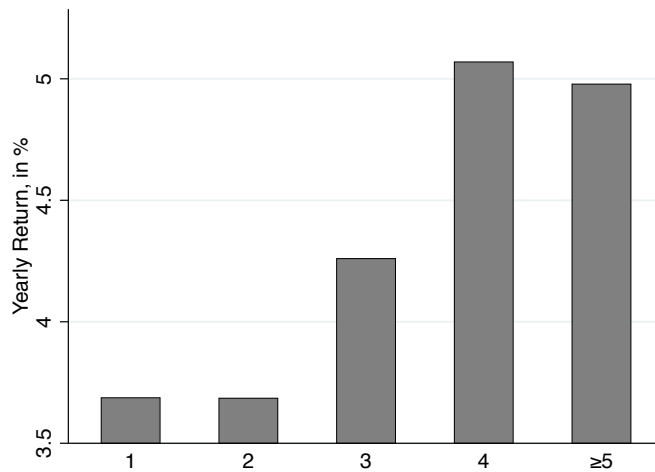


FIGURE VII. Headline Rate by Complexity Levels (Number of Features)

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.

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

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.³⁷

5.2 Product Complexity and Product Risk

We now explore how product complexity relates to potential losses for the investor. Figure VIII shows the share of issuance volumes that expose investors to complete losses by level of complexity.³⁸ More complex products more frequently expose the investor to complete losses.

We then conduct 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

³⁷See Table A10 in the online appendix for the coefficients of the same regressions weighted by volumes.

³⁸We use *number of features* as the measure of complexity.

Table IV. Headline Rate and Product Complexity

	Headline Rate (spread to benchmark), in %					
	(1)	(2)	(3)	(4)	(5)	(6)
# Features	0.504*** (0.052)	0.291*** (0.067)				
# Scenarios			0.434*** (0.058)	0.107** (0.054)		
Length (1,000 characters)					1.849*** (0.606)	0.174 (0.304)
<i>Controls</i>						
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
<i>Observations</i>	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

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. 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. 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 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.

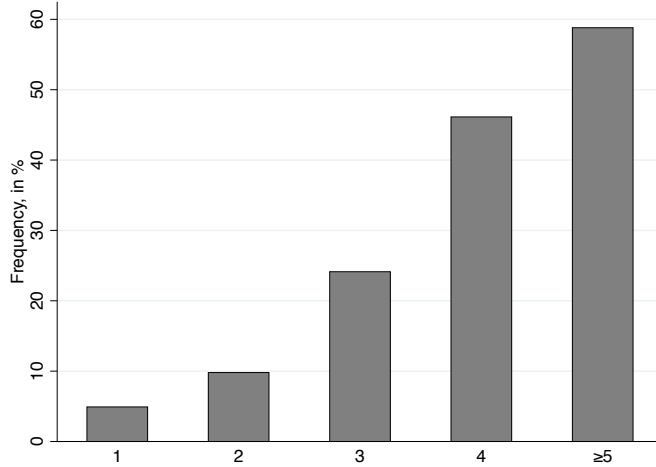


FIGURE VIII. Share of Volumes Exposing Investors to Complete Losses by Complexity Levels (Number of Features)

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 negative 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, Swedish, Norwegian, Danish, Polish, Czech, and Eurozone interest rates.³⁹ We estimate the following OLS model:

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

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

³⁹Figure A8 in the online appendix displays the evolution of these interest rates over our sample period.

Table V. Loss Exposure and Product Complexity

	Investor Exposed to Complete Losses (Indicator Variable)					
	<i>Logit</i>					
	(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)
<i>Controls</i>						
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
<i>Observations</i>	53,541	45,163	53,541	45,519	53,541	45,519
<i>Pseudo R</i> 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 potential total 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.⁴⁰ 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-

⁴⁰We 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 A12 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. Therefore, banks offset two-thirds of the decrease in interest rates in the headline rates.

In columns (3) and (4) 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 again negative and significant for these specifications. Hence, banks are more inclined to offer products exposing investors to complete losses in a low interest rate environment. The coefficient of the interaction in column (4) 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. In columns (5) to (7), 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 encountered high interest rates prior to the introduction of the euro.

5.4 Bank Characteristics

We now explore whether the level of complexity of products varies with bank characteristics.

A. Bank Customer Base

We first study whether product complexity varies with the type of households that banks target.

Table A8 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

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

	Headline Rate		Loss Exposure		Product Complexity		
	(Spread)		(Indicator)		# Features	# Scenarios	Length
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Benchmark Rate	-0.640*** (0.182)	-0.669*** (0.211)	-0.506*** (0.182)	-0.656*** (0.188)	-0.133*** (0.043)	-0.070 (0.048)	-33.137*** (9.632)
Benchmark Rate × Historical Rates		-0.026 (0.048)		-0.144** (0.064)	-0.040*** (0.007)	-0.049*** (0.016)	-6.566*** (1.635)
<i>Controls</i>							
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
<i>Observations</i>	26,352	25,516	45,513	43,851	51,259	51,259	51,259
R^2	0.224	0.228	0.464	0.460	0.257	0.407	0.356

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, 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 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.

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 our control group, which comprises commercial banks. This result illustrates how the banks targeting the less sophisticated client base offer the most complex products.

Table VII. Complexity Measures and Distributor Customer Base

	# Features (1)	# Scenarios (2)	Length (3)
Savings Bank	0.240** (0.120)	0.474** (0.208)	41.673 (25.865)
Private Banking	0.202** (0.084)	0.078 (0.136)	16.062 (11.931)
<i>Controls</i>			
Underlying FE	Yes	Yes	Yes
Maturity	Yes	Yes	Yes
Volume	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
<i>Observations</i>	53,541	53,541	53,541
R^2	0.093	0.144	0.115

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 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 level. *, **, and *** represent statistical significance at the 10%, 5%, and 1% confidence levels, respectively.

B. Bank Risk Taking

We then investigate whether product complexity correlates with proxies for bank risk taking.

We consider three proxies for bank risk taking: leverage, reliance on wholesale funding, and balance sheet exposure to Greek sovereign debt.⁴¹ Tables A15 and A16 in the online appendix show how product complexity, headline rate, and exposure to complete losses all positively correlate with these three proxies for bank risk taking. These regressions control for bank size, as measured by $\log(\text{total assets})$. In addition,

⁴¹Data 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.

we find that banks that possess an investment banking division are more likely to offer products that expose investors to complete losses.

5.5 Product Profitability

A. Complex Products Markups

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.^{42,43} 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.⁴⁴

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.⁴⁵ 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. Column (2) documents that products that expose investors to complete losses offer a significantly larger markup: 0.78 percentage points per year. Columns (3) to (5) present the coefficients obtained when regress-

⁴²Table A18 in the online appendix provides detailed information on each product we price and the corresponding undisclosed markup we calculate.

⁴³Our 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.

⁴⁴Arnold et al. (2016) analyze the pricing of credit risk in retail structured products.

⁴⁵This 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					Ex-post Performance				
	Product Yearly Markup, in %					Product Yearly Return, in %				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Headline Rate (spread)	0.056* (0.028)					-0.051 (0.059)				
Loss Exposure		0.782** (0.294)					-3.496*** (1.164)			
# Features			0.343*** (0.117)					-0.398*** (0.140)		
# Scenarios				0.196** (0.082)					-0.626*** (0.212)	
Length (1,000 characters)					1.256** (0.600)					-2.601** (1.181)
<i>Controls</i>										
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	0.838	0.823	0.820	0.816	0.584	0.588	0.590	0.593	0.590

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.

ing 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 0.34 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 (4) and (5) 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. Coefficients are of the same magnitude and significance in OLS regressions weighted by volumes (see Table A17 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 A18 in the online appendix).⁴⁶ In addition, we conduct several robustness checks on the asset pricing methodology in the online appendix (Table A18).

B. Ex-Post Performance of Complex Products

Our database includes the final performance of 48% of the participation products that matured before 2011, which amounts to 7,500 products.⁴⁷ This performance is before disclosed fees. 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%, and 15% offered a negative return. We regress this *ex post* performance on the headline rate on the indicator variable equal to 1 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 also control for exposure to

⁴⁶This is consistent with some distributors marketing “zero-fee”-structured products, for which profitability accrues exclusively from the embedded markup.

⁴⁷Because 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.

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. On the other hand, column (7) indicates that risky products underperformed, as some of the downside risk materialized. Columns (8) to (10) 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 markup.

6 Discussion

The primary motive for financial institutions to develop innovative and complex securities is still debated. Issuers may tailor securities to improve risk sharing (Allen and Gale, 1994; Duffie and Rahi, 1995), or conversely, to increase opportunities for speculation (Simsek, 2013), screen for unsophisticated investors (Carlin, 2009), extract agency rents (Biais et al., 2015; Biais and Landier, 2015), or cater to yield-seeking investors.

This section compares the empirical results of our study to the broad predictions of two theories of financial complexity in retail finance: (1) banks issue complex securities to complete markets for households and improve risk sharing and (2) banks use complexity to cater to investors' yield-seeking propensity.

6.1 Theoretical Frameworks

A. Risk Sharing

First, banks may design complex products to better share risk among households with heterogeneous levels of risk aversion. Structured product flexible payoffs allow

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

banks to offer a menu of products with different return and risk profiles, ranging from risk-free products to products with high risk and high expected returns. In this setup, banks adjust the risk profile of structured products by adding distinct payoff features to match investors' needs, which increases product complexity. For instance, by adding a reverse convertible feature, banks can increase product risk while offering a higher return in some scenarios. Conversely, some other payoff features, such as capital protection, may allow risk-averse investors to invest in financial assets that would otherwise not be attractive to them.

For the risk-sharing hypothesis to hold, however, we need to make two assumptions. First, households face a limited set of securities that does not provide them with enough heterogeneity in terms of risk profile. Second, it is costly for households to adjust the risky share of their portfolio. An alternative way for households to share risk would then be through the payoff design of their investment.⁴⁹

B. Salience

Alternatively, banks may use complexity to cater to yield-seeking investors.

If retail investors are salient thinkers in the sense of Bordalo et al. (2012), they tend to overweight headline rates and neglect risk when headline rates deviate significantly from the benchmark interest rate. Banks therefore have an incentive to enlarge the spread between structured product headline rates and the benchmark interest rate. To this end, banks exploit the flexibility of structured product design by including payoff features that either make it less likely to obtain the headline rate or that increase downside exposure. This accumulation of features, which increases product complexity, allows banks to offer higher headline rates. The first prediction of this theoretical framework is that complex products and products that expose investors to losses should offer higher headline rates.

Bordalo et al. (2015) show that salient investors overweight more high headline rates when interest rates are low, as they think in proportions. The second empirical

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

prediction is therefore that headline rate and product complexity should be higher in a low interest rate environment.

By increasing product complexity, banks can also shroud features that are equivalent to a contingent fee, hence allowing banks to offer even a higher headline rate through a “waterbed” effect. Inderst and Obradovits (2016) show how, when shrouding meets salience in a market for goods, firms are more likely to compete on prices rather than quality. Applied to our set-up, this framework implies that banks are more likely to compete on headline rates at the expense of higher product risk when complexity, hence shrouding, increases. This complementary theory extends the predictions of the salience framework. First, in the time series, complexity should increase along with headline rates. Second, salient thinkers are more likely to buy complex products that offer high headline rates. Third, as shrouded fees are not fully passed through to higher headline rates, complex products and products that offer a higher headline rate should be more profitable to the banks.

6.2 Disentangling Theories

At first glance, selling complex products to households is consistent with a risk sharing rationale.

Structured products indeed allow retail investors to buy and sell options while it is difficult for them to do it directly, as it requires managing a margin account, and European regulators restrict these types of transactions. Buying options typically reduces the risk of the underlying investment, while selling options increases its risk. Hence, banks would use complex products to offer the risk exposure that best matches investors’ risk preferences by tailoring the payoff function.

However, mapping the results from our study into this framework requires making a series of strong hypotheses. First, adding a payoff feature should correspond to better fitting the risk profile demanded by some households. However, a large share of payoff features, such as path-dependence features, have an ambiguous effect on the product risk profile. Second, the increasing complexity of product payoffs we observe requires either a slow diffusion of innovative features over several years, or an

increasingly complex demand for risk profiles from retail investors. Third, the larger share of risky products offered during the financial crisis calls for retail investors to be less risk-averse than investment banks in this environment. Finally, savings banks, which target low to middle-income households, offer more complex products. Those households, who tend to be neither affluent nor investment-savvy, would have to be the ones with the most complex risk preferences.

On the other hand, our results map precisely into the predictions of the salience theory.

First, complex products offer significantly larger headline rates, which is consistent with the prediction that banks use complexity to increase the headline rate, and thereby make this dimension salient. The creative marketing strategies for these products, which largely focus on the product headline rate, is also supportive of a catering rationale.

Second, complex products are more likely to include a risky feature. This is consistent with banks shrouding features that create contingent charges. Shrouding these payoff features, in turn, favors an equilibrium where the headline rate is salient (Inderst and Obradovits, 2016).

Third, banks rely more on complexity and offer products with relatively higher headline rates and more risky features during periods of low interest rates. This result is in line with the prediction that banks cater more for yield-seeking investors when interest rates are low (Bordalo et al., 2015). This effect is stronger in countries where interest rates were high historically compared to the European average.⁵⁰

We also find that product markups are increasing with both product complexity and headline rates, as predicted by Inderst and Obradovits (2016) and (Bordalo et al., 2015). In addition, *ex post* performance is negatively correlated with complexity, which is in line with banks taking a larger markup on these products, thereby hurting their performance.

Our results point to certain banks catering more to investors through complexity

⁵⁰This result is consistent with past experience affecting households' propensity to reach for yield, as it affects other types of financial decisions (Malmendier and Nagel (2016)).

than others. The most complex products are offered by savings banks, the clients of which are more likely to be salient thinkers (Solomon et al. (2014); Stango and Zinman (2014)). These households might as well be more sensitive to shrouding. Offering more complex products to investors more prone to salience is consistent with the prediction from Bordalo et al. (2015) and Inderst and Obradovits (2016). Moreover, the use of complexity is correlated with proxies for bank risk taking, such as balance sheet leverage, asset exposure to Greece sovereign debt, or reliance on wholesale funding. This suggests that the retail market for structured products might have been another channel for banks to implement profitable but risky strategies.⁵¹

7 Conclusion

We use unique data on a large market of investment products marketed to households and develop measures of product complexity, headline rate, 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 financial complexity and find, first, that more complex products offer higher headline rates 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. In addition, savings banks, which target low- to middle-income households, offer products that are more complex on average. 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.

Compared to the predictions from the theoretical literature, our results support the view that banks use complexity to cater for yield-seeking investors. Our findings raise questions about the adequate regulation of complex instruments and investor

⁵¹The main risks for banks are arguably reputation and relationship risk, as they typically hedge their positions.

protection in retail finance.

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Imprint and acknowledgements

Note

This paper was the winner of the ESRB's inaugural Ieke van den Burg research prize in 2015. The paper was selected by a committee of the Advisory Scientific Committee comprising Viral Acharya, Markus Brunnermeier, Martin Hellwig, Marco Pagano and Andre Sapir. The committee considered the paper to be very good, very interesting, and highly original, with great policy relevance. The committee also felt the paper to be in keeping with the spirit of the ESRB's new research prize, which honours the memory of Ieke van den Burg by recognising outstanding research conducted by young scholars on a topic related to the ESRB's mission.

Acknowledgements

This study is based on Claire Célérier's dissertation submitted to the Toulouse School of Economics and on Boris Vallée's dissertation submitted to HEC Paris. We greatly appreciate comments and suggestions during our discussions with friends and colleagues, including Malcolm Baker, Bruno Biais, Laurent Calvet, John Campbell, Bruce Carlin, Shawn Cole, Thierry Foucault, Xavier Gabaix, Robin Greenwood, Denis Gromb, Michel Habib, Sam Hanson, Samuel Hartzmann, Ulrich Hege, Johan Hombert, Victoria Ivashina, Marcin Kacperczyk, David McLean, Stefan Nagel, Terrence Odean, Matthew Rabin, Jean-Charles Rochet, Paola Sapienza, Antoinette Schoar, Andrei Shleifer, Paolo Sodini, Erik Stafford, Jeremy Stein, Adi Sunderam, David Thesmar, and numerous conference and seminar participants. We are very grateful to LexiFi for allowing us to use its pricing tool, and we thank Jean-Marc Eber for his interest in our project. We thank Europlace for financial support. Claire Célérier acknowledges financial support from SFI and URPP Finreg. All errors are ours alone.

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ISSN 2467-0677 (online)

ISBN 978-92-95081-41-3 (online)

DOI 10.2849/9466 (online)

EU catalogue No DT-AD-16-014-EN-N (online)