What Drives Financial Complexity? A Look into the Retail Market for Structured Products *

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Abstract

By focusing on the highly innovative retail market for structured products, we investigate the drivers of financial complexity. We perform a lexicographic analysis of the term sheets of 55,000 retail structured products issued in 17 European countries since 2002. We observe that financial complexity has been steadily increasing, even after the recent financial crisis, and that financial complexity is more prevalent among distributors with a less sophisticated investor base. We then compute the fair value of a representative sample of products and show that the hidden markup in a product is an increasing function of its complexity. Finally, by using a difference-in-differences approach that relies on staggered ETF entries, we find that financial complexity increases when competition intensifies. These findings are consistent with financial institutions strategically using complexity to mitigate competition.

Keywords: Household Finance, Financial Literacy, Financial Complexity, Retail Structured Products, Product Differentiation

JEL codes: I22, G1, D18, D12

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1 Introduction

Abundant anecdotal evidence suggests that the complexity of household financial products has dramatically increased over the last twenty years. Innovative products have been introduced continuously on the asset and liability sides -for example for mutual funds, credit cards, and mortgages -while financial literacy and sophistication seem to remain low (Lusardi et al. (2009), Lusardi et al. (2010)). Is there an actual trend towards increasing financial complexity in retail products? If so, what drives this increase? To answer these questions, we focus on a specific market that has been experiencing sustained growth and innovation in the last decade: the retail market for structured products. We first develop an index of product complexity, which we apply to a comprehensive dataset of 55,000 retail structured products sold in Europe. We observe through this index that financial complexity has been increasing over time. We consider several demand-side explanations for this stylized fact: catering to changing needs and preferences, a trend to more risk sharing and better market completeness, and a gambling motive. Observations from our data do not corroborate the first three explanations. We therefore focus on supply side based explanations, specifically on the strategic use of complexity that has been stipulated in various theoretical contributions in finance (e.g., Carlin (2009) and Carlin and Manso (2011)) and in industrial organization (Ellison (2005) and Gabaix and Laibson (2006)). We find evidence consistent with the theoretical explanations that emphasize motives such as increasing search costs or price discrimination. First, we document that product complexity is associated with higher product profitability for banks and lower performance for investors. Second, using issuance level data spanning 15 countries over the period 2002-2010, we find that product financial complexity increases when competition intensifies. Our paper provides the first empirical test of the positive relationship between heightened competition and increasing financial complexity, which has been postulated in the theoretical literature (Carlin (2009)).

The first objective of this paper is to try to measure the possible increase in financial complexity as accurately as possible. We document a trend of increasing financial complexity by examining the product term sheets of all the retail structured products issued in Europe since 2002 through a lexicographic analysis. We find that this trend continues even after the financial crisis. A major empirical challenge of our analysis lies in measuring product complexity in an accurate and relevant way in the highly diverse market of retail structured products. To do so, we develop an algorithm that precisely strips and identifies each feature embedded in the payoff formula of all the past and currently existing structured products in the retail market. We define the complexity level of a given product as its total number of features. The rationale of our approach is that the more features a product has, the more complex it is for the investor to understand and compare. We also use the number of characters used in the pay-off formula description, as well as the number of potential scenarios, as robustness checks for our measure of complexity. The finding of increasing financial complexity over time is robust to any of these complexity measures.

The second objective of the paper is to explore possible explanations for this increasing complexity in the retail market for structured products. We begin by investigating demand side explanations. First, we examine whether this observation results from catering to changing preferences or consumer needs. However, we find that none of the many variables and controls we use detects any time trends or shifts in the composition of the market for structured products. Second, we analyze whether rising financial complexity is linked to increasing market completeness or better risk sharing opportunities. However, this hypothesis should imply that complexity is more prevalent among products for sophisticated and affluent investors, who should obtain the largest benefit from such opportunities. However, our data indicate the opposite: institutions that target unsophisticated clients, such as savings banks, offer relatively more complex products. Additionally, specific product features - e.g., monetizing a cap on the rise of the underlying index above a certain threshold - and more surprisingly monetizing the possibility to take a loss if the underlying index drops below a certain threshold - are more frequent when implicit volatility is high, potentially driving up the average product complexity during these periods.

Therefore, in our attempt to understand the origins of increasing complexity, we turn to arguments explaining the use of financial complexity as a strategic tool to mitigate competitive pressure. Based on ample theoretical literature, we test in particular two hypotheses: markup of complex products should be relatively higher, and complexity should increase when competition intensifies. We first establish a relationship between financial complexity and product profitability. We price a subset of very homogenous retail structured products based on liquid underlying assets with Least Square Monte Carlo and then examine the explanatory power of product complexity for markups. We find that the more complex a product is, the more profitable it becomes. Based on the realized ex-post performance of 48% of the products that have matured, we also show that the more complex a product is, the lower its final performance. These findings are consistent with higher complexity being associated with a higher profit for the distributing intermediaries. Second, we empirically investigate the effect of a competition shock on financial complexity. We implement a difference-in-differences methodology to assess the impact of Exchange Trading Fund (ETF) entries, on complexity. The entry of ETFs represents an increase of competition for retail structured products, as ETFs can be offered as a substitute to these products. We find that the same distributor offers more complex products in countries where ETFs have been introduced than in countries where they have not been introduced. A specification with bank-year fixed effects further mitigates potential concerns over reverse causality between ETF entries and financial complexity. As an alternative estimation of the impact of a change in the competition environment on complexity, we show that the average complexity of the product offer from the same distributor is higher in markets where the number of competitors has increased, which is again consistent with distributors adapting to the competitive environment. This result is robust to controlling for country level financial sector profitability, which could drive endogenously the number of competitors.

We use a new dataset that contains detailed information on all the retail structured products that have been sold in Europe since 2002. This database has key characteristics that facilitate text analysis, as well as a clean identification strategy in an empirical industrial organization study. It covers 17 countries and 9 years of data, with both strong inter-country and inter-temporal heterogeneity. It includes more than 300 competitors. At the issuance level, a detailed description of payoffs, information on distributors, and volume sold are available.

There are several reasons to study the financial complexity dynamics in the retail market for structured products; one of them is the sheer size of the market. In Europe alone, outstanding volumes of retail structured products add up to more than EUR 700bn, which is equivalent to 12% of the mutual fund industry. Assets under management have been steadily growing, despite the financial crisis, with the US market meeting USD 160bn of retail structured product issuance since 2010. As direct participation in financial markets has been structurally decreasing in Europe, structured products often represent a privileged way of getting exposure to stock markets. In addition, information asymmetry is high between innovators, investment banks structuring the products, and the final consumer: the mass-market retail investor. We find many examples of products that pile up many complex features which are then marketed to savings bank customers, who are less likely to be sophisticated.[1] This finding illustrates the gap between supply-side complexity and demand-side sophistication. In this study, we define financial complexity from the investor's point of view, meaning how difficult it is for him or her to understand a product and compare it with possible alternatives.[2]

Our work contributes to several fields of the literature. First, our paper builds on the theoretical literature on financial complexity. Ellison (2005) and Gabaix and Laibson (2006) describe how inefficient product complexity emerges in a competitive equilibrium. To account for the complexity increase in financial products, Carlin (2009) and Carlin and Manso (2011) develop models in which the fraction of unsophisticated investors is endogenous and increases with product complexity. Carlin (2009) shows that as competition intensifies, product complexity increases. Our paper is the first to test direct implications

[1] See section 3 for an example.

[2] We do not take the structuring bank point of view: how difficult it is to create a given product. A product simple to understand can be challenging to structure. For instance, derivatives on real estate, although easily understood by retail investors are extremely difficult to structure for banks, mainly for liquidity reasons. The incentive is clear for a structuring bank to be the only one to price a product as it allows charging the monopolistic price.

from these models by empirically assessing the role of competition in the evolution of financial complexity. More specifically, our work contributes to the emerging field on complex securities (Griffin et al. (2013), Ghent et al. (2013), Carlin et al. (2013), Amromin et al. (2011), Sato (2013)).

Our project also complements the literature on the role of financial literacy and limited cognition in consumer financial choices and bank strategies. Bucks and Pence (2008) and Bergstresser and Beshears (2010) explore the relationship between cognitive ability and mortgage choice. Lusardi and Tufano (2009) find that people with low financial literacy are more likely to take poor financial decisions. Complexity might amplify these issues. This paper also relates to the recent interest in the role of financial intermediaries in providing product recommendations to potentially uninformed consumers (Anagol and Cole (2013)).

Our paper also adds to the literature on structured products. Hens and Rieger (2008) theoretically reject completing markets as a motive for complexity by showing that the most represented structured products do not bring additional utility to investors in a rational framework. Empirical papers on the retail market for structured products have focused on the pricing of specific types of products. Henderson and Pearson (2011) estimate overpricing by banks to be almost 8%, on the basis of a detailed analysis of 64 issues of a popular type of retail structured products. This result challenges the completeness motive, as it will come at too high a cost.

In terms of policy implications, our work stresses the need to assess product complexity independently from risk. An additional step may be to impose a cap on complexity or to foster the standardization of retail structured products to limit the competition dynamics we observe. Such measures suppose for the regulator to develop and use a comprehensive and homogenous measure of product complexity beforehand.

Our paper is organized as follows: we begin in section 2 by providing background information on the retail market for structured products. Our methodology for building a complexity index is described in section 3, as well as the trend towards increasing complexity. Section 4 considers possible demand-side explanations for the increase in financial complexity. Section 5 explores the strategic use of financial complexity. Finally, section 6 concludes.

2 The Retail Market for Structured Products

2.1 Background

Retail structured products regroup any investment products marketed to retail investors with a payoff that is determined following a formula defined ex-ante. They leave no place for discretionary investment decisions along the life of the investment.[3] Our study excludes products with pay-offs that are a linear function of a given underlying performance, e.g., ETFs. Retail structured products are typically structured with embedded options. Although these products largely rely on equities, the exposure one can achieve with them is very broad: commodities, fixed income or other alternative underlyings, with some example of products even linked to the Soccer World Cup results.

Below is an example of a product commercialized by Banque Postale (French Post Office Bank) in 2010:

> *Vivango is a 6-year maturity product whose final payoff is linked to a basket of 18 shares (largest companies by market capitalization within the Eurostoxx50). Every year, the average performance of the three best-performing shares in the basket, compared to their initial levels is recorded. These three shares are then removed from the basket for subsequent calculations. At maturity, the product offers guaranteed capital of 100%, plus 70% of the average of these performances recorded annually throughout the investment period.*

This example illustrates the complexity of a popular structured product, which contrasts with the likely level of financial sophistication of the average client of Banque Postale. The

[3] Retail structured product do not give any discretion to the investor in terms of exercising options, which is done automatically, as opposed to mortgages.

biased underlying dynamic selection and the averaging of performance across time makes the product complex to assess in terms of expected performance.

The retail market for structured products has emerged in 1996 and has been steadily growing from then on. In 2011, assets under management of retail structured products amount to about 700 billion euros in Europe, which amounts to nearly 3% of all European financial savings, or 12% of mutual funds' asset under management. Europe, with a market share of 64%, and 357 distributors in 2010 is by far the largest market for these products. However, the US and Asia are catching are growing quickly. The US market has met USD160bn of retail structured product issuance since 2010.[4] Regulation, both in terms of consumer protection and bank perimeter is the main explanation for the difference in size between the European and the US markets. Consumer protection imposes retail structured products to have a high minimum investment in the US, typically USD250,000. Furthermore, the Glass Steagall Act limited internal structuring of these products until its repeal in 1999. The predominant role of personal brokers as financial advisers in the US, as opposed to bank employees, may also have played a role.

The growth of this market has been fostered by an increasing demand for passive products, as the added value of active management has become more and more challenged (Jensen (1968) or Grinblatt and Titman (1994)). Structured product profitability for the banks structuring and distributing them also plays an important role (Henderson and Pearson (2011)). Indeed, on top of disclosed fees, some profits are hidden in the payoff structure that is hedged at better conditions than offered to investor. The incentive to hide markup within the product has been increased in Europe by recent MiFID regulation that requires distributors to disclose commercial and management fees. In addition, retail structured products, when packaged as securities or deposits, can offer a funding alternative for banks, and a possible way of transferring some specific risks to retail investors.[5]

The organization of the retail market for structured products is largely explained by

[4]Source: Euromoney Structured Retail Products.

[5]Recent issuances often allow bank to transfer tail risk to retail investors, as product will incur losses only in case of a strong decrease of the underlying, such as a 30% decrease in the index.

the nature of the structuring process. Since these products are very complex to structure, only large investment banks have the exotic trading platform required to create them. But no equivalent barriers of scale exist on the distribution side, and distribution channels are more dispersed. Consequently, entities distributing the products to retail investors are often, but not necessarily, distinct from investment banks that structure them. These products have been marketed by a large range of financial institutions, from commercial banks, savings banks and insurance, to organizations active in wealth management and private banking. Many providers emphasize in their marketing efforts their expertise in structuring even when they do not actually structure the products, but only select them and implement a back-to-back transaction with an entity that can manage the market risk. Therefore, competition is playing out at two levels: between structuring entities, which sell to distributors, and between distributors, which sell to retail investors. Our analysis focuses on the latter, as we are interested in the dynamics of financial complexity in retail markets.

The regulatory framework is a key determinant of the development and structure of this market, in which both bank supervision and investor protection exist. European national regulators, which are subordinated to a supranational regualtor since 2011, the European Securities and Markets Authority (ESMA), have been increasingly attentive to protecting retail investors. The European Commission has developed a single Europe-wide regulatory framework defined by the UCITS Directive. However, until 2010, national regulators mainly focused on disclosure requirements, which may have amplified issues of an asymmetric relationship between intermediaries and clients by mandating information requirements that were too abundant or too technical for clients, such as backtesting. MiFID regulation introduced client classification and corresponding products appropriateness. Investors are warned when they choose a product deemed unusual or inappropriate. However, some national regulators appear to mix complexity with risk, and focus on the latter. For instance, in his latest guidelines about structured products (REF 2010), the French regulator limits product complexity if and only if investor capital is at risk.

2.2 Data

Our original data stems from a commercial database, called *Euromoney Structured Retail Products*, which collects detailed information on all the retail structured products that have been sold in Europe since the market inception (1996). As no benchmark data source exists, it is difficult to determine the exact market coverage of the database. However, some country-comparisons suggest that the database provides a comprehensive repository of the industry.[6]

The retail market for retail structured products is divided into three categories: flow products, leverage products, and tranche products. We focus on tranche products, which are non-standardized products with a limited offer period, usually 4 to 8 weeks, and a maturity date. These products have the largest investor base, the highest amount of assets under management (they stand for 90% of total volumes), the highest average volumes, and exhibit the largest heterogeneity in terms of pay-offs. We therefore exclude flow products, which are highly standardized and frequently issued products, as they represent a high number of issuances with very low volumes (sometimes even null).[7] We also exclude leverage products, which are short term and open-ended products. In tranche products, investors typically implement a buy and hold strategy, because there are significant penalties for exiting before the maturity of the product. As of December 2010, the total volume (number) of outstanding structured tranche products was respectively EUR 704bn (41,277) in Europe.[8] Data are available for 17 countries in Europe, and cumulated volumes per country since the market inception are given in Table 1. Italy, Spain, Germany, and France dominate the market in terms of volume sold, making up for 60% of the total. We match this data with additional information on providers (Bankscope and hand-collected data), market conditions (Datastream) and macro-economic country variables (World Bank) at

[6]For instance, the coverage on Danish products is 10% larger than that of a hand collected data on the same market in Jorgensen et al. (2011)

[7]These products, for instance bonus and discount certificates, are very popular in Germany. Indeed, hundreds of flow products are issued every day and 825,063 of them have been issued from 2002 to 2010. However, their size is only 20,000 Euros on average, against 8.8 million euros for the core market that we consider.

[8]If we include leverage and flow products, the number of outstanding structured products are 406,037 products and volumes are EUR 822bn.

the time of issuance.

INSERT TABLE 1

Since 2002, the retail market for structured products has seen the emergence of two major trends: both the volume sold (Figure 1) and the number of distributors have significantly increased (from 144 in 2002 to 357 in 2010), with a slight decrease since the financial crisis. (Table 2). The market is divided between commercial banks, private banks, saving banks and insurance companies, implying a heterogeneous investor base.

INSERT FIGURE 1

Table 2 provides summary statistics on the underlying type, distributor type, marketing format, volume and design of the products in our dataset. We observe that equity is the most widespread exposure, either through single shares, basket of shares or equity indices. Although slightly decreasing over time, the fraction of products with an equity underlying represent 77% of products from our sample. In terms of format, structured notes are becoming increasingly popular, as opposed to collateralized fund type product. This trend is likely to be motivated by banks by banks trying to raise funding through these instruments. With the number of products increasing, the average volume per product has been decreasing over the last ten years. Finally, products where the investor is guaranteed to receive at least her initial investment, which were dominant at the beginning of the period, are becoming less popular and represent around half of the products in the recent years.

INSERT TABLE 2

3 Measuring Financial Complexity

3.1 Classifying Payoffs

This subsection describes how we measure product complexity in the retail market for structured products. We develop an algorithm that converts the text description of 55,000 potentially unique products into a quantitative measure of complexity in a robust and replicable manner. This algorithm identifies features embedded in each payoff formula and counts them. The rationale of our approach is that the more features a product has, the more complex it is for the investor to understand and compare.

We first develop a typology of all the features retail structured products may be composed of. This typology classifies the features along a tree-like structure. The eight nodes of the tree represent the steps that an investor may face to understand the final payoff formula of a retail structured product. Only the first node, the main pay-off formula, is compulsory. The following nodes cover facultative features. Example of features are: reverse convertible, which increases the investor exposition to a negative performance of the underlying, or Asian option, where the value of the payoff depends on the average price of the underlying asset over a certain period of time. Each one of the eight nodes of our typology includes on average five features. Therefore, our methodology covers more than 70,000 combinations of features and hence differentiated products. Table 3 displays the structure of our typology by representing each node of the tree. We provide the description for each node and definition for each pay-off feature in the appendix. Our typology covers exhaustively the features that presently exist in the market.

INSERT TABLE 3

In a second stage, an algorithm scans the text description of the final payoff formula of all the 55,000 products and counts the number of features they contain.[9] This algorithm first runs a lexicographic analysis by looking for specific word combinations in the text description that pinpoint each feature we have defined in our typology. The algorithm identifies more than 1,500 different pay-off features combinations in our data. Then we simply count the number of features to measure complexity. This approach assumes that all the features defined in our typology are equally complex. Like for any index, the equal weighting is a simplification, but it avoids subjective weighting biases. Given the depth of

[9]Each formula description has been translated by the data provider, and only contains the necessary information to calculate the performance of the product.

the breakdown we develop, the potential error introduced by equal weighting is probably a minor concern when compared to indexes built on a small number of components.

Table 4 shows how our methodology applies to two existing products. While the first product is only made of one feature at the compulsory node: *Call*, the second exhibits three distinct features: *Call*, *Himalaya*, and *Asian option*, indicating a higher level of complexity. The length of the product descriptions also appears to be an increasing function of the number of features.

INSERT TABLE 4

Our methodology allows us to identify and measure the complexity of the payoff formula of all the past and currently existing retail structured products, but also that of virtually any new products that might be invented and marketed in the future. A simple typology based on the final product formula with corresponding levels of complexity would indeed not have been satisfying given the high diversity we observe. Our methodology is especially appropriate as far as it allows us to capture the piling up of features we observe in the market. Furthermore, our algorithm can easily be updated to take into account future developments of the market. Updating our algorithm only requires adding a branch to the feature tree when some new features are created.

3.2 Results

Figure 2 shows the unconditional average complexity of products from our sample by year. Complexity appears to be an increasing function of time, with almost no decrease in its growth trend following the financial crisis.

INSERT FIGURE 2

To examine this graphical evidence more formally, we regress our complexity measures on a linear time trend, as well as year fixed effects in a second specification. We control for a battery of products characteristics, such as underlying type, distributor, format, country, volume and maturity. Results are shown in Table 5. Both specifications indicate that complexity has been steadily and significantly increasing over time. The coefficient of the linear trend is positive and highly significant. Coefficients on the year fixed effects are increasing with time.

INSERT TABLE 5

Despite the widespread view that the financial crisis has driven down the complexity of financial instruments, we find that this is not the case for products targeted to retail investors. This fact points towards product structuring being driven by the supply side of the market, not the demand side.[10] This result is robust to the measure of complexity we use. In section 5 and 6, we explore an industrial organization explanation for this increase in complexity.

We then look into the evolution of the *distribution* of complexity. Figure 3 plots the distribution of products from our sample along our complexity index, for three sub-periods. The increase of complexity is not driven only by a fraction of the distribution of complexity, but instead increases across all complexity quartiles. Over time, we observe a decrease in the share of simple products, as well as an increase in the share of the most complex products. This empirical fact is consistent with banks piling up new features on existing pay-off combinations.

INSERT FIGURE 3

3.3 Robustness Checks

As a first robustness check for our measure of complexity, we use the length of the formula description, measured by the number of characters. Table 4 illustrates that the more complex a product is, the higher the number of words needed to describe its payoff.

[10] The rise in complexity does not appear to be driven by banks providing additional insurance in the products. On the contrary, reverse convertible features, that expose investors to downside, are more frequent after the crisis than before. This increased popularity is likely to relate to a higher volatility that increases the value of selling options. We discuss further this point in the next session.

As a second robustness check, we consider the number of different scenarios that impact the final return formula. The same product formula can indeed vary depending on one or several conditions at maturity or along the life of the product. This measure is close to counting the number of kinks in the final payoff curves, as a change of scenario translates into a point of non-linearity for the pay-off function.[11] We quantify the number of scenarios by identifying conditional subordinating conjunctions such as "if", "when" and "whether" in the text description of the payoff formula. Overall, we observe a correlation around 0.6 between our three different complexity measures, which illustrates that they are coherent and still complementary.

We observe the same increasing trend over the year when using the length of descriptions or the number of scenarios as a complexity measure. Figure B.0 in the appendix provides graphical evidence for this result.

We also consider the possibility that a change in regulation, more specifically the implementation of the MiFID directive on November 1st, 2007, might have led to a different methodology for describing pay-offs, therefore creating a measurement error. Our result are robust to this regulation shock for the following reasons. First, the text description we use is extracted from the prospectus and translated by our data-provider based on the same and stable methodology. This description is therefore not impacted by the requirement of additional disclosures, such as backtesting and warnings. In addition, the most significant yearly increase in complexity we observe is anterior to this regulatory change. Finally, we control the time-consistency of the text description by identifying manually products with identical pay-offs features, before and after the MiFID directive was implemented. We find that payoff descriptions remain very similar, and include around the same number of characters.

[11] However this measure also accounts for path dependency that is not captured by the number of kinks of the final pay-off function.

4 Demand-Side Explanations of Financial Complexity

This section discusses possible explanations for the increase in complexity we observe that are based on various aspect of the demand side and their possible evolution.

4.1 Catering to Changing Needs and Preferences

A first potential explanation for the increase in complexity that we document is that it is driven by changing consumer preferences or investor needs and a desire of intermediaries to cater to these varying patterns by offering a different portfolio of products. If some product formats or underlying assets require a relatively high complexity, and become popular for instance for tax efficiency reasons, a change in the product mix to cater to such changes could explain the evolution of complexity. Also, assuming that only sophisticated investors use complex products, if unsophisticated investors leave the market, we would observe a rise in average complexity. These explanations have in common that they predict a time-varying composition of the portfolio of structured products that are available and marketed.

Evidence from data goes against this potential explanation. First, as shown in Table 5, this trend of increasing complexity is robust to conditioning on format, underlying, distributor and country fixed effects, as well as maturity changes. Therefore our stylized fact cannot be explained by hypotheses that imply a time-varying composition of the market for structured products in terms of product and distributor mix.

Second, volume appears to be a poor predictor of complexity. Total issuance volume follows a hump shape over our sample period, while complexity has been increasing over the whole period. Whereas volumes in 2011 are close to the 2006 level, complexity is significantly higher. Moreover, conditioning on product issuance volume does not remove the significance of the year fixed effects in column 2 of Table 5. Also, the decrease in issuance volume after 2007 is in line with other risky products such as ETFs, and does not suggest a massive flee from these types of products vs. simpler ones within the risky financial assets. Overall, change in the composition of the population of retail investors is likely to be low.

4.2 Risk Sharing and Increasing Completeness

A second potential explanation for the increase in complexity is that banks are progressively offering products that better suit retail investor demand for risk sharing opportunities and increasingly complete markets. However, several stylized facts in our data appear inconsistent with this explanation.

First, we find that the most complex products are not offered to the most sophisticated and affluent investors, who should possess both the skills required to apprehend these products and the diversified portfolio that these products could complement.

We use the type of the investor's financial institution to proxy for investor sophistication and wealth. Savings banks provide financial services mainly to rural and low to middle class households, whereas private banks mainly focus on high-income individuals. Hence, we group distributors into four categories: savings banks, commercial banks, insurance, and private banks / wealth managers.[12] Table C.1 in the appendix describes the 20 main distributor groups in 2010 and their type. Among them, three are savings banks (the Deutsche Volksbanken and Raiffeisenbanken, the Deutsche Sparkassen and the Spanish Caja de Ahorros), 12 are commercial banks (Deutsche Bank, RBS, KBC etc.) and 2 are private banks or wealth managers (Garantum and J.P.Morgan).

INSERT TABLE 6

Table 6 displays statistics on the level of complexity per type of distributor. We observe that savings banks, while targeting unsophisticated investors, distribute on average more complex products than the other types of distributors: commercial banks, insurance companies, and private banks/wealth managers. We confirm this unconditional statistics by regressing the product complexity on distributor type dummies, controlling for product

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

characteristics. The second panel in Table 6 shows that savings bank products are significantly more complex than the products of the control group, which consists of commercial banks. Moreover, the coefficient on the savings bank dummy is higher than the one on private banks, which target more sophisticated investors.

Second, market conditions appear as an important driver of structuring choices. While, under the reasonable assumption that retail investors are more risk averse than financial institutions, the demand for protection should increase with market volatility, we observe the opposite: the share of products exposed to tail risk increases with volatility.

INSERT FIGURE 4

Figure 4 illustrates the evolution of both short volatility products - products that perform well if volatility decreases during the life of the product - and the implied volatility index on European stock markets (VSTOXX).[13] [14] We observe that the ratio of short volatility products increases when implicit volatility is high, an effect that is observable even after the financial crisis. This finding suggests that instead of matching investors' needs, financial institutions exploit market conditions to inflate investor expectations, as products including selling options can offer higher returns, although at a higher risk, when volatility is high.

Finally, if complex products indeed better match demand of retail investors, they should have been marketed as soon as they were invented. Although research and development of financial products is costly and therefore can take some time to implement, innovations we observe in the retail market for structured products are minor and could have been quickly disseminated.

[13]The most popular underlying in the market is the Eurostoxx 50

[14]Features corresponding to a short volatility exposures are: reverse convertible, cap, knock out, and callable products. Reverse convertible products are implicitly selling a put option, leading to downside exposure to the underlying. On the opposite, cap, knock-out and callable features limit the product upside when market volatility is high.

4.3 Gambling Products

A third explanation for complex products is that these products would represent gambling opportunities. Gambling within financial markets is a documented behavior in the literature (Kumar (2009)). Although this hypothesis can hardly account for the *increase* in complexity unless there would be an increasing appetite for gambling, it is worth considering as an explanation for the existence of complex products. First, a large fraction of the products in our sample presents the opposite payoff of a lottery: they provide a small gain with a high probability, and a large loss with a small probability, as they are implicitly selling options. These pay-offs could however be consistent with prospect theory, if retail investors underweight the real probability of extreme events. Second, our analysis does not cover the type of products that would be most amenable to gambling motives, namely pure optional products, such as turbos and warrants, which present lottery like pay-offs (low probability of a very high gain). These products appeal to a small investor base that is not representative for the retail structured market. Another problem for the gambling hypothesis is that some households invest a significant fraction of their financial wealth into these products, for instance through life insurance products. For example, life insurance contracts, where investments are concentrated and these products are popular, constitute more than 26% of household financial wealth in Europe.[15] In addition, the numerous examples of households suing banks in the UK, France, Germany, Switzerland and Spain, due to poor product performance, seem to contradict the hypothesis that this market essentially exists for households that want to gamble. For example, in September 2008 CHF700 million invested in capital guaranteed products structured by Lehman Brothers were lost, which led to litigation.

All these potential explanations for the increasing complexity in retail financial products appear to not withstand the stylized facts we observe in our data. A final possible explanation is that in the retail market for structured products banks compete through complexity. The next section details a relevant theoretical framework and provide evidence

[15]Source: Household Finance and Consumption Survey, available at www.ecb.europa.eu.

consistent with this hypothesis.

5 The Strategic Use of Financial Complexity

5.1 Theoretical Considerations

Our research hypothesis is that firms use complexity to mitigate competitive pressure. This section discusses theoretical models on product complexity in competitive markets that support this hypothesis. There are two main rationales for consumer obfuscation, which is a purposeful increase in complexity to make a product pricing or design harder to understand. One rationale is to increase search costs, which leads to oligopoly pricing (e.g., Salop and Stiglitz (1977); Varian (1980); Stahl (1989)) or even monopoly pricing (Diamond (1971)). Another rationale is to price discriminate between sophisticated and unsophisticated consumers by adding expensive facultative "add-ons" or "shrouded attributes" to a base good (Ellison (2005) and Gabaix and Laibson (2006)). When applied to financial markets, this price discrimination strategy translates into making price disclosure more complex (Carlin (2009), Carlin and Manso (2011)). In the following subsections, we discuss the theoretical literature and develop two testable implications. First, complex products should be more profitable than simpler ones. Second, when the level of complexity is endogenously determined by firms, complexity should increase along with competition to preserve markups.

A. Increasing Search Costs to Charge Oligopoly Prices

Consumer search costs impact markups, as they allow firms to charge oligopoly prices (see Diamond (1971); Salop and Stiglitz (1977); Varian (1980); Stahl (1989)). Stahl (1989) considers a model of search with perfect recall in which only a fraction of consumers incur a search cost. The model produces price dispersion. As search costs increase, price dispersion changes smoothly from marginal cost prices to monopoly prices, and firm profits increase.

Product complexity in retail finance is likely to increase search costs. Indeed, it takes more effort to compare the pricing of financial products with three payoff features than products with only one feature, as there are more dimensions to simultaneously compare on. An alternative approach that links search costs with product differentiation is the model from Hortacsu and Syverson (2004) in the index mutual fund industry. Their model incorporates investors' taste for specific attributes, and search frictions that deter investors from finding the fund offering them the highest utility.[16] This theoretical background leads to our first empirical prediction that more complex product should exhibit higher markups.[17]

B. Price discriminating through complexity

In Ellison (2005), and Gabaix and Laibson (2006), firms offer a base good that can be coupled with "add-ons", or "shrouded attributes" that are more profitable. Firms sell products to two categories of investors: sophisticated and unsophisticated ones. Sophisticated consumers observe the price of the shrouded attributes, whereas unsophisticated consumers do not. In equilibrium, only unsophisticated investors buy shrouded attributes in addition to the base good. By providing clear information on shrouded attributes a firm would only attract sophisticated consumers who pay less (Ellison (2005)), or decrease the fraction of unsophisticated consumers (Gabaix and Laibson (2006)) and therefore reduce profits. Consequently, firms offer complex products at equilibrium and make large profit despite the competitive pressure.

The discrimination strategy between sophisticated and unsophisticated consumers applies well to retail market for structured products. In this market, financial firms can sell a base good, for instance a call-type product, to which they add facultative payoff features, such as a cap on the gain at maturity, or an Asian option feature.[18]

[16]Products from our study are likely to simultaneously appeal to some taste and increase search frictions.

[17]Robert and Stahl (1993) in a search cost model with perfect recall show that as competition increases, firms decrease the level of information they disseminate in the market. Consumers are ex ante identical and firms can inform some of them through advertising at a cost increasing and convex in the fraction of informed consumers. As competition increases, the incentive to inform consumers decreases since the chance to capture informed consumers decreases. Rational firms tend to withdraw from the advertising competition and content themselves with their local monopoly of uninformed consumers. One could regard advertising as an action that educate investors about the price structure of retail financial products and hence reduce their complexity. However the assumption on advertising cost is not directly transposable to the market of this analysis.

[18]In an asian option, the value of the payoff depends on the average price of the underlying asset over a certain period of time as opposed to at maturity.

When applying price discrimination to financial products, Carlin (2009) develops a model in which the share of unsophisticated/uninformed consumers is endogenous and results from the level of complexity chosen by the financial firms offering the products. Financial firms create ignorance by making price disclosure more complex. Sophisticated investors or experts are fully informed about prices independent from the level of complexity, and buy from the firm offering the lowest price, while uninformed investors purchase the good from a randomly chosen firm. Hence, each firm both captures a fraction of the unsophisticated consumers, and can win demand from the experts. When competition intensifies, the chance to obtain a share of the experts decreases. To compensate for this decrease in potential profits, each firm increases product complexity and therefore the fraction of unsophisticated investors they capture. Firms increase strategically product complexity to preserve profits in the face of a higher competition.

Finally, we write a simple model presented in the appendix. This toy model is derived from Carlin (2009), but differs in that consumers are heterogeneously distributed across firms and may face switching costs. Therefore, the price and complexity strategy of firms depends on the fraction of consumers they capture *ex-ante*. With two categories of investors, experts and uninformed consumers, and the presence of switch costs, this model is at the intersection of the two strands of theoretical literature we have explored. Firms' tradeoff is between offering a complex product at a high price to the fraction of uninformed consumers they capture or competing for experts. This tractable model leads to three results we observe in our data: first, firms targeting unsophisticated consumers offer relatively complex products, second, complex products are more profitable than simple ones, and third, firm entry leads to increasing complexity.

5.2 Financial Complexity and Product Profitability

This section presents calculations of the markups of the 101 retail structured products that were issued in Europe in July 2009 with the Euro Stoxx 50 index as an underlying. We define markup as the difference between the offering price and the fair market value we calculate through a local volatility model. We find that markups are increasing with product complexity.

We focus on a restricted sample in terms of period and underlying in order to maximize accuracy and within sample comparability. First, opting for a sample of products with the same underlying ensures that heterogeneity in complexity only comes from the pay-off formula, and not from the underlying assets. In addition, the choice of a single index as an underlying allows us to discard any measurement errors in terms of implied correlation, as opposed to products linked on a basket of stocks. Second, the Eurostoxx 50 index is one of the most liquid financial indexes, and is the most frequent underlying asset for the products in our total sample. Eurostoxx 50 options with various moneyness and maturities trade daily on several exchanges with tight bid-ask spreads. High quality and detailed volatility data is therefore available from the market places, which is key for pricing accurately these complex products.

Third, by focusing on a short time window we ensure comparability of market conditions. We choose July 2009 as the number of issuances and heterogeneity of products linked to Euro Stoxx 50 during this month was the highest recorded since market inception. Focusing on a specific month and estimating all the products issued during this month is a consistent first step of our analysis.[19] The next step of our analysis will be to do the same exercise for July 2007 and July 2011, to confirm that our results are robust when we expand the estimation period. We could also test whether the relationship between markup and complexity varies across time.

A. Methodology

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 following diffusion:

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

[19]This methodology is more rigorous than choosing products randomly over different dates, as we could not efficiently control for time fixed effects due to the small size of the sample.

where S_t is the price of the underlying, $\sigma(t; St)$ 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 yield.

Using a local volatility specification, in contrast to a simple Black and Scholes formula, is key for pricing the considered products since they frequently possess deeply out of the money embedded options, such as an implicit sale of put options, or a cap on the final pay-off.[20] Models of stochastic volatility may improve the accuracy of the pricing (Dumas et al. (1998)) but are challenging to calibrate. Moreover, the purpose of our pricing exercise is to identify at which price structuring banks can hedge the pay-off, which they assess using local volatility models. Retail structured products pay-offs are largely path dependent. To account for this specificity, we use the Least Square Monte Carlo (LSM) methodology (Longstaff and Schwartz (2001)), which is well recognized and implemented by both academics and professionals. Performing accurately this calculation-intensive methodology that includes both volatility surface and path dependence was helped by the use of the Lexifi pricing tool.

Our implied volatility data is from Eurex, the largest European derivative exchange. We use the EUR swap rate curve to discount cashflows, which we obtain from Datastream. The daily stock prices and the historical values of the interbank rates (Euribor) are collected from Bloomberg. We finally compute a constant dividend yield from future prices that are also extracted from Bloomberg.

We estimate the hidden markup of the products as the difference between the issuance price, which is typically indicated on the prospectus of the product, and the fair price we calculate with our asset pricing methodology. Appendix B provides detailed information on each product we price, as well as the corresponding hidden markup we calculate.

B. Results

We find an average markup of 2.4% without including disclosed entry and management fees. Our estimates are lower than in Henderson and Pearson (2011), and we obtain 27

[20] Henderson and Pearson (2011), or Jorgensen et al. (2011) use constant volatility but look mainly at products with at the money options.

products with negative markups. All these negative markups correspond to products that provide funding to the bank issuing them, as they are not collateralized. Therefore, we should discount the fair value by the funding cost of the bank for these products. When discounting, we do not observe anymore negative markups, except for two cases. Additionally, when we add disclosed fees to hidden markups, we obtain an average profitability of 6.0%.

The purpose of our pricing exercise is to identify a relationship between product complexity and profitability. Thus, the cross section of markups within our sample matters the most, while a systematic error would not bias our analysis. We estimate the following cross-sectional regression of product markups on our main complexity proxy:

$$YearlyMarkup_i = \alpha \times \mathit{NbPayoffs}_i + \beta \times X_i + \epsilon_i \tag{2}$$

where $YearlyMarkup$ is the difference between the issuance value and the fair value we estimate, normalized by the product maturity, *NbPayoffs* is the number of payoffs embedded in the structured product formula as a measure for its complexity, and X_i is a vector of product level controls. As discussed earlier, we include a dummy *Credit Risk* for products that are non-collateralized, as they provide funding to the issuer.

INSERT TABLE 7

Table 7 presents the results. We find a statistically and economically significant relationship between complexity and profitability. This result is highly significant despite the small sample size. One additional feature in a payoff formula translates into an increase in the yearly markup by 0.28 percent of the notional. With an average maturity of 5.5 years it corresponds to an increase of around 1.5 percent of the notional of the total markup, or half of the average markup. This result does not depend on the complexity measure we use: an additional scenario and a one standard deviation variation in the length of the description leads to an increase in the yearly markup of respectively 0.27 and 0.24 percent (see appendix). To address composition effect concerns, we add additional controls to our baseline specification. Column 2 of Table 7 shows the coefficients when we control for distributor fixed effects.[21] In column 3, we control for the primary feature fixed effects, to ensure that our result is not driven by some specific types of products. Column 4 adds fixed effects for the 4 most frequent facultative features.[22] In column 5, we add disclosed fees to the hidden markup, and use this total profitability measure as the dependent variable. Finally, column 6 shows an additional robustness check: we use markup calculated with a Partial Differential Equation methodology as a left-hand side variable.[23] For all these specifications, we find a significant and robust positive relationship between product complexity and markups. These results show that the more complex a product is, the more profitable it is for the bank to structure it. The economic significance of this result is high, explaining the strong incentives banks have to issue complex products.

C. Ex post performance

Finally we test whether the relatively high level of *ex ante* markup at the issuance of more complex products translates into relatively low *ex post* performance. We find a negative relationship between product complexity and performance, which is consistent with higher complexity being associated with higher profits that are absorbed by the banks.

Performance is an important criterion to analyze the impact of financial complexity on investor surplus, as higher hidden fees could be offset by superior product performance. Our database includes the final performance for 48% of the growth products that matured before 2011.[24] We substitute yearly performance to yearly markup in the previous specification:

$$YearlyPerf_i = \alpha \times \mathit{NbPayoffs}_i + \beta \times X_i + \epsilon_i \tag{3}$$

Where *YearlyPerf* is the ratio of the final pay-off minus the issuance price, over the issuance price, which is then normalized by the product maturity, *NbPayoffs* is the number

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

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

[23]We obtain a smaller number of observations as some products present a computational challenge due to their path-dependent nature.

[24]Germany and Austria are excluded from this analysis as the performance ex post is not available for these countries. We only include growth products, as they offer a unique flow at maturity, and therefore do not pay any coupon during the life of the product.

of payoffs embedded in the structured product formula as a measure of its complexity and X_i is a vector of product level controls. Because our sample covers around 7,500 products and spans over several years, we are able to include underlying and year fixed effects.

INSERT TABLE 8

Table 8 presents the OLS regression coefficients of the annualized performance on product complexity. We observe a significant negative correlation between a product complexity and its performance, despite our battery of controls. Complexity seems therefore to reduce investor surplus ex-post. To ensure that different levels of risk related to the levels of complexity do not drive our results, we control for feature fixed effects, which for instance capture whether the initial capital invested is guaranteed at maturity. Our results hold for each of the three measures of complexity. We also restrict the sample to Eurostoxx 50 products in columns (2), (4), and (6) to maximize comparability of performance, but the result does not change.

5.3 Complexity and Competition: The impact of ETF entry on complexity

In this section, we exploit the staggered entry of a new but simple product across European countries - Exchange Traded Funds or ETFs - as an exogenous shock to the competition environment of the retail market for structured products. This shock has first been used by Sun (2014) in the US to study the price impact of competition on active management investment products.

The entry of ETFs represents an increase of competition for retail structured products, as ETFs can be offered as a substitute to these products. Both ETFs and retail structured products belong to the segment of passive management funds. Additionally, ETFs are simple products whose price is easily observable by sophisticated investors. Their linear pay-offs make them easy to comprehend for an investor and their cost - which consists in disclosed management fees -is also easy to observe and low. These characteristics make

ETFs an excellent fit for the theoretical framework we previously described. The prediction is that entries of simple products should help banks to discriminate between sophisticated and unsophisticated investors.

A. Measuring ETF entries

The first challenge of using ETF entries in Europe lies in the identification of the date when ETFs were first commercialized across European countries. Even more relevant to our analysis is the date when investors' attention turned to these products. We use Google Trend, focusing on the use of the search-term "ETF", to accurately capture this timing. The country-level time series provided by this tool allows us to identify in which month "ETF" started being used as a search-term by Internet users. This time corresponds to when the ETF asset class starts drawing interest from potential investors in the considered country. To avoid measurement errors, we check that "ETF" does not mean anything other than "Exchange Traded Fund" in the different languages of our sample countries. We also check in Factiva that this first occurrence in Google Trend is contemporary to media coverage. This analysis reveals that ETF entries have been staggered across European countries, with entry years spanning from before 2004 (when Google Trend starts) for Italy to 2010 for Poland.

B. Difference in differences on the impact on complexity

We exploit the staggered nature of ETF entries to implement a difference-in-differences methodology, allowing a clean identification of the impact of the competition shock on complexity.

INSERT FIGURE 6

Figure 6 plots the average evolution of complexity before and after ETF entry in each country. While there is no clear trend prior to the entry, the average complexity in the retail market for structured products rises significantly after ETF entry.

We confirm this graphical evidence by estimating the following model, at the country-year and distributor-country-year level:

$$Y_{d,c,y} = \alpha + \beta \times Treated \times post + \delta_y + \theta_c + \gamma_d$$

where $Y_{d,c,y}$ is the average complexity for distributor d, in country c and in year y. $Treated$ is a dummy equal to one for the countries where ETFs have been introduced, and *post* is a dummy equal to one for the years after the first occurrence of ETF as a search-term. As more than half of the product distributors are present in several countries, we put distributor fixed effects (γ_d) in addition to year (δ_y) and country fixed effects (θ_c). Thus, we effectively identify the difference in offer for the same distributor when ETFs are available as potential substitutes to structured products and when they are not.

INSERT TABLE 9

Results are shown in Table 9. We find a positive and significant impact of ETF entries on the aggregate level of complexity. As we are using distributor fixed effects, we show that the same distributors offer more complex products in countries where ETFs are available than in countries where they are not. This result is even robust to distributor-year fixed effects, which minimizes concerns over the potential self-selection of the distributors active in a given year.

We also find that the effect of ETF entry on product complexity is robust when excluding the most simple products of our analysis, i.e. the products with only one pay-off, in column X. This result shows that ETF entries do not only create a substitution effect, but that they actually contribute to an aggregate increase in complexity.

C. Endogeneity Concerns for ETF Entries

Quantitatively, we also re-run our difference-in-differences methodology, including interaction terms between treated and a dummy equal to one for the year preceding the ETF entries. While we find that the initial interaction term is still statistically significant, this additional term is not significant, which points toward the absence of a pre-existing increasing trend of complexity prior to the ETF entry. Moreover, discussions with practitioners point towards ETF entries being mainly driven by institutional details at the country level.

One of the main drivers is the obtention of eligibility for tax-efficient schemes, such as life-insurance.

5.4 Complexity and Competition: Alternative Estimation

A. Methodology

We use panel data at the country and distributor level spanning respectively 15 countries and 486 distributors to empirically test our theoretical framework.[25]

We measure competition intensity by computing the number of competitors in the retail market for structured products per year in each country. This measure corresponds to our theoretical framework that focuses on market entries, as opposed to distribution of market share. To ensure that the distributors we identify are independent competitors, we match our data with Bankscope and regroup distributors by holding companies. We regroup savings banks of the same network, such as Sparkassen in Germany or Cajas in Spain into the same provider group as their geographical coverage does not overlap nationally. Hence, we identify 471 competitors that have been active one or more years over the period 2002-2010 in the retail market for structured products.

We measure average financial complexity with two different panels: one at the country-year level and another one at the distributor-country-year level. For each panel we compute a volume weighted average of the previously described complexity indexes: number of payoff features, description length and number of scenarios.

B. Country Panel

We estimate the following panel data regression.

At the country level

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

where $Y_{c,y}$ is the average complexity in country c in year y. $Competition_{c,y}$ is the number

[25] Two countries are excluded due to low representativeness: Hungary and Poland. Volume sold since inception has been lower than 10 million euros in these countries. Norway is not taken into account over the period 2008-2010 due to a ban on selling structured products to retail investors.

of distributors active in the retail market for structured products in country c and year y. Country fixed effects θ_c control for time invariant determinants of product diversity, such as the size of the market for example. Year fixed effects δ_y control for aggregate shocks or common trend in the retail market for structured products. We compute robust standard errors. The parameter of interest is β, which measures the impact of an increase in the number of competitors on product diversity. We observe in column 1 that the level of financial complexity increases as competition intensifies. This result is consistent with our theoretical framework. We substitute the number of distinct product types sold in country c in year y as a dependent variable in column 2, and find that this increase in complexity is concomitant with a higher differentiation of the product offer at the country level. We find that the number of product types also increases when competition intensifies.

INSERT TABLE 10

C. Distributor-Country Panel

To deepen our analysis, we conduct a similar estimation at the distributor-country level. This level of analysis allows us to put distributor fixed effects and absorb unobserved variables that are unvarying at the distributor level. More precisely, we estimate the following model:

$$Y_{d,c,y} = \alpha + \beta * Competition_{c,y} + \delta_y + \theta_c + \phi_d + \epsilon_{d,c,y} \tag{5}$$

This specification partially addresses endogeneity concerns. Indeed, we look at how distributors adapt depending on the level of competition of the market in which they participate. We exploit the fact that 51% of the providers participate in more than one market. Sources of endogeneity at the country and distributor level are therefore addressed by our fixed effects.

We observe that distributors adapt indeed their offer to the level of complexity: the same distributor will offer relatively more complex products in a relatively more competitive national market. This result is consistent with competition having a causal effect on financial complexity.

D. Robustness

To ensure that our results are not driven by a systematic measurement error in our complexity index, we implement robustness checks for each of our results, using both the number of scenarios and the length of the description. These tests reinforce our results as the coefficients remain of the same sign and significant in almost all our specifications. Results are displayed in the online appendix.

6 Conclusion

Identifying the drivers of financial complexity is key to our understanding of financial markets. We use unique data on the European retail market for structured products to study financial complexity, allowing a neat identification of its location and drivers. In this paper, we first develop an innovative measure of the complexity of retail structured products based on a lexicographic analysis of the prospectus of 55,000 products. This measure shows that complexity has been significantly increasing in this sizable market. We then consider several explanations for this increase. Composition effects, or increasingly complete markets for retail investors, do not appear as satisfactory explanations when analyzing our data.

We therefore focus on the hypothesis that distributors use complexity to mitigate competitive pressure. Our theoretical framework, which includes a toy model in the appendix, yields two main empirical implications that we test using our dataset. Uninformed consumers tend to overpay products when they cannot observe their prices, as documented by several papers (Anagol and Cole (2013), Anagol and Kim (2012), Choi et al. (2010)). We calculate the fair-value and markup of a representative sub-sample of our products using Monte-Carlo simulations with local volatility diffusions. We find that the more complex a retail structured product is, the more profitable it is for the bank. An ex-post performance measure of retail structured products confirms that these relatively high level of markup translates into relatively low performance for more complex products.

Finally, when investigating the relationship between complexity and competition in our data, we find evidence of a positive correlation. Based on country and distributor panel data for 15 countries over the period 2002-2010, we find that complexity increases when product market competition intensifies. In combination with our results on product performance, this finding represents evidence of a potentially pernicious effect of competition and raises the question of regulation and investor protection in retail finance.

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A Figures

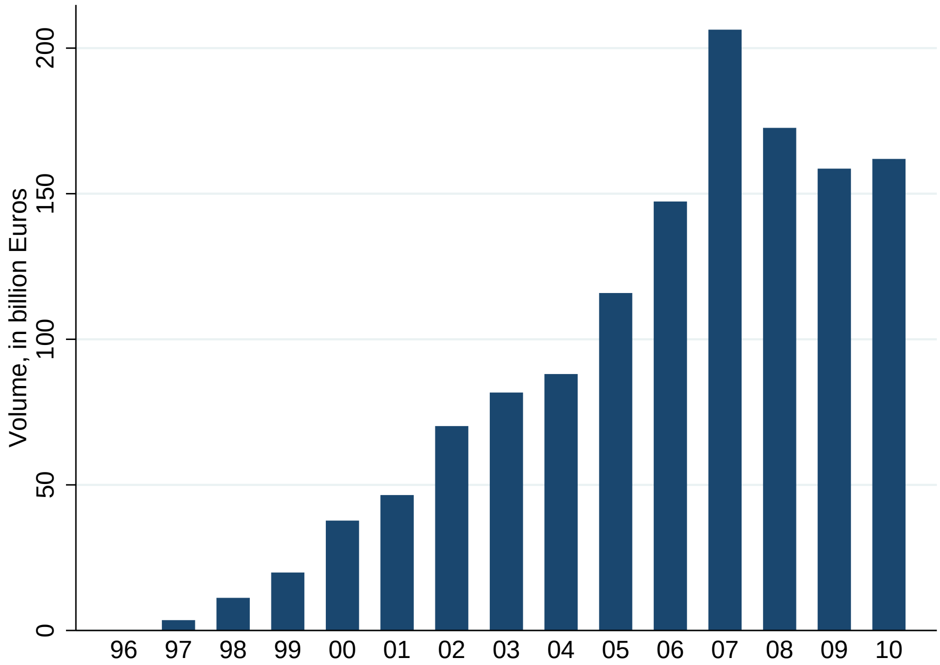

Figure 1. Volume Sold per Year, in billion euros

This figure shows volume issuance of tranche retail structured products over the period 1996-2011 in the European market, in billion Euros. Included countries are the following: Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Hungary, Ireland, Italy, Netherlands, Norway, Poland, Portugal, Spain, Sweden, UK.

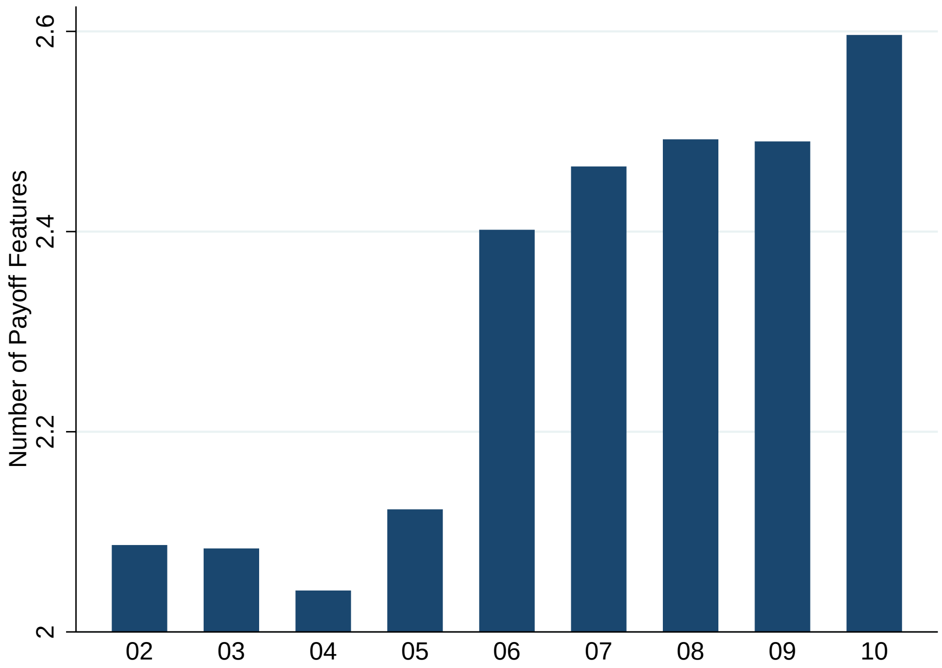

Figure 2. Average Product Complexity by Year

This figure shows the average complexity of retail structured products by year. The sample covers 55,585 products from 17 European countries. Complexity is measured as the number of features embedded in each product payoff formula. We obtain this complexity measure through a lexicographic analysis of the detailed text description of the final payoff formula(from Euromoney SRP).

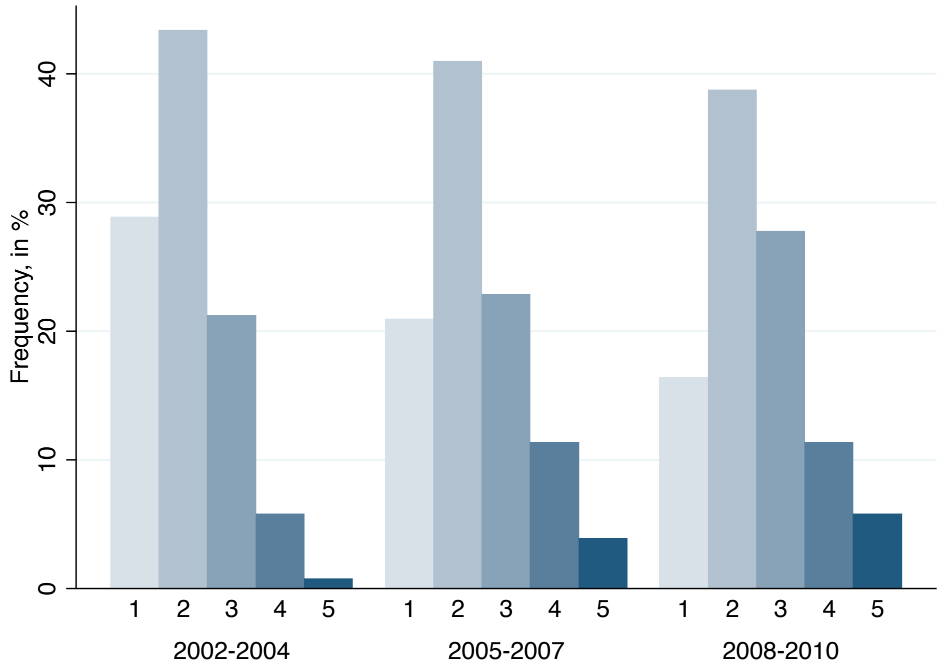

Figure 3. Evolution of the Distribution of Product Complexity

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

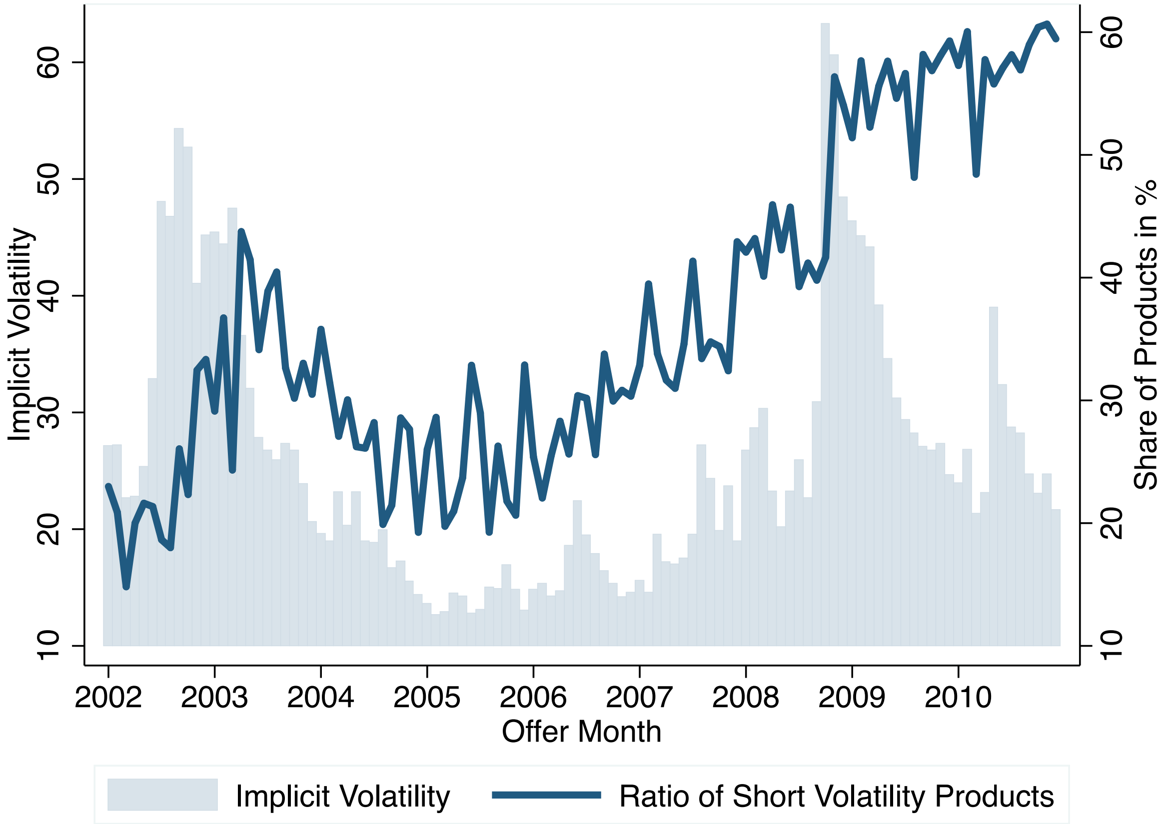

Figure 4. Ratio of Short Volatility Products and Implicit Volatility

This figure shows the share of short volatility products issued each month and the level of the implicit volatility index over the 2002-2011 period. Short volatility products include products with one or several features that induce either a loss when the underlying index drops below a certain threshold or a cap on the final payoff when the underlying index is above a certain threshold. These features are defined in the Appendix. Implicit volatility is measured by the implied volatility index on European stock markets (VSTOXX).

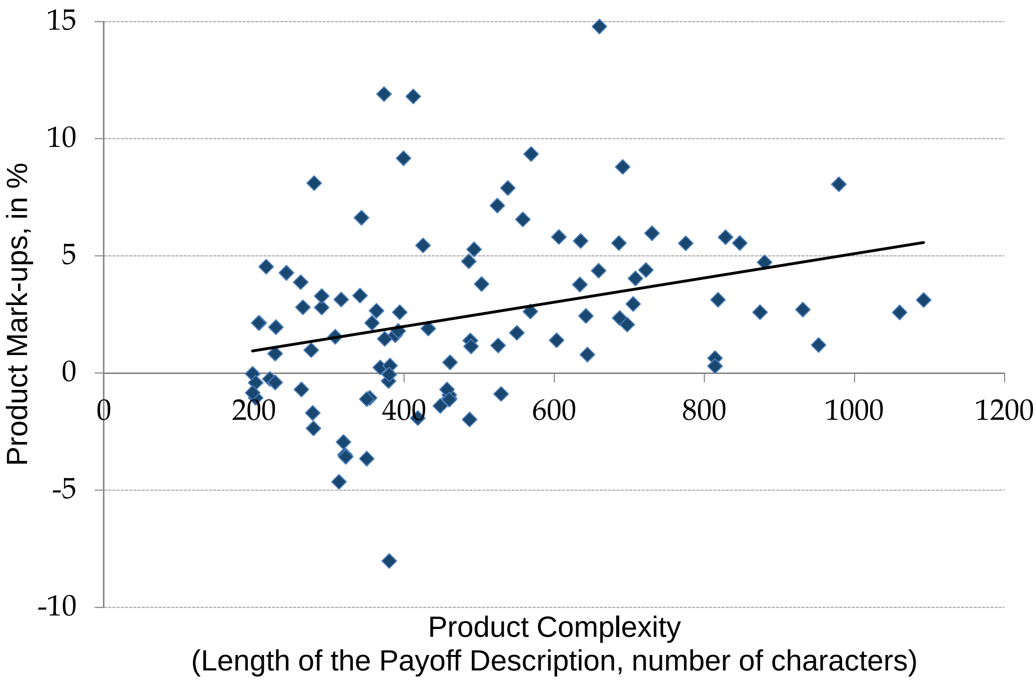

Figure 5. Description Length and Product Markups

This figure plots the markup of a product over its level of complexity for 101 products issued in July 2009 and indexed to the Eurostoxx 50. Complexity is measured by the number of characters used in text description of the payoff formula of each product. We define markup as the difference between the offering price and the fair market value we calculate through a local volatility model. We use the Longstaff and Schwartz OLS MonteCarlo pricing methodology in order to account for path dependence (Longstaff and Schwartz (2001)). Markups are expressed in % of notional, length in number of characters. Pay-off descriptions are from Euromoney SRP.

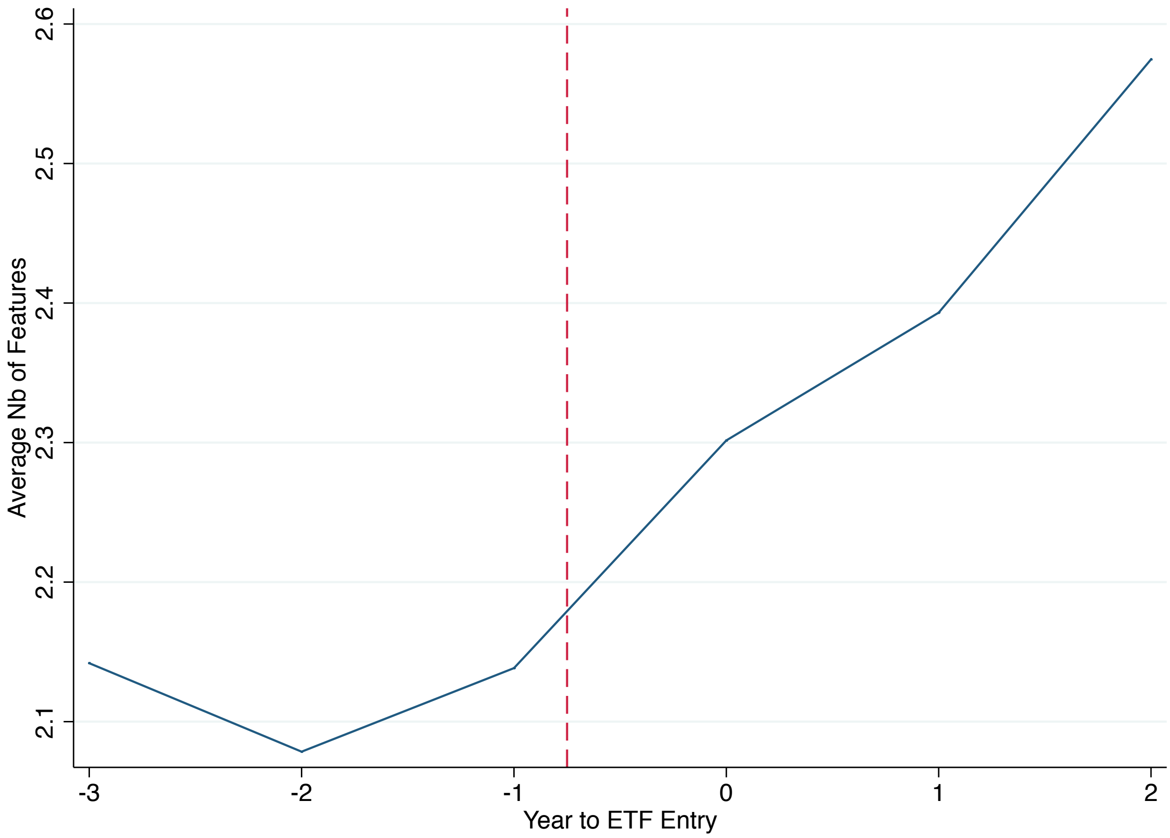

Figure 6. ETF Entry and Financial Complexity

This figure plots the markup of a product over its level of complexity for 101 products issued in July 2009 and indexed to the Eurostoxx 50. Complexity is measured by the number of characters used in text description of the payoff formula of each product. We define markup as the difference between the offering price and the fair market value we calculate through a local volatility model. We use the Longstaff and Schwartz OLS MonteCarlo pricing methodology in order to account for path dependence (Longstaff and Schwartz (2001)). Markups are expressed in % of notional, length in number of characters. Pay-off descriptions are from Euromoney SRP.

B Tables

Table 1. Country-Level Summary Statistics

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

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

Table 2. Product and Distributor Summary Statistics

Variable	2002-2004 (1)	2005-2007 (2)	2008-2010 (3)	Full Sample (4)
Underlying Type (in %)				
Equity	82.1	77.5	70.5	76.6
Single Index	*36.2*	*35.9*	*36.9*	*36.1*
Single Share	*2.9*	9.5	7.5	8.1
Basket	*42.9*	*32.1*	*26.1*	*32.3*
Interest Rate	5.1	4.5	13.9	6.6
Commodity	0.6	5.5	4.0	4.5
FX Rate	1.8	3.1	4.6	3.2
Other	10.4	9.5	6.9	9.1
Distributor Type, Number (Market Share, in%)				
Commercial Banks	102 *(40.8)*	132 *(41.0)*	133 *(37.4)*	172 *(36.7)*
Saving Banks	21 *(8.4)*	20 *(6.2)*	24 *(6.7)*	28 *(6.0)*
Private Banks	94 *(37.6)*	123 *(38.2)*	152 *(42.7)*	202 *(43.1)*
Insurance	23 *(9.2)*	30 *(9.3)*	31 *(8.7)*	40 *(8.5)*
Other	10 *(4.0)*	17 *(5.3)*	16 *(4.5)*	27 *(5.8)*
Total	250	324	357	471
Product Format (in %)				
Non Collateralised Assets	61.0	83.9	88.4	81.7
Security	*44.6*	*69.7*	*76.6*	*67.7*
Deposit	*16.5*	*14.2*	*11.8*	*14.0*
Collateralised Assets	39.0	16.1	11.6	18.3
Life Insurance Product	*6.9*	*6.3*	*4.6*	*6.0*
Fund	*31.8*	*9.6*	*7.0*	*12.1*
Pension	*0.3*	*0.2*	*0.1*	*0.2*
Volume (in million Euros)				
Mean	38.6	18.6	14.9	20.5
10th percentile	5.9	3.5	2.0	3.2
90th percentile	84.0	30.0	27.0	40.0
Product Design				
Capital Guarantee (in %)	82.3	62.0	55.4	60.9
Average Maturity (in years)	5.0	4.3	4.0	4.2

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

Table 3. Typology of Retail Structured Product Features

	Families of Facultative Features						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Initial Subsidy	**Underlying Selection**	**Exposure Modulation, Downside**	**Exposure Modulation, Upside**	**Path Dependance**	**Exotic condition**	**Early Redemption**
	↓	↓	↓	↓	↓	↓	↓
Main Feature							
1. Call →	*Final Product:*						
2. Put→	*Each product includes one main feature*						
3. Spread→	*and 0 to 7 facultative features*						
4. Pure Income→	*with a maximum of 1 per family*						
5. Digital→							
6. Floater→							

This table describes how a pay-off formula is broken down into distinct features. Each family of facultative features contains features that are mutually exclusive. A structured product possesses exactly one main feature, which defines the primary structure of the product. Details of each feature are provided in appendix.

Table 4. Measuring Complexity

	Example 1: Unigarant: Euro Stoxx 50 2007	**Example 2: Vivango Actions Mars 2017**
Details		
Year	2002	2010
Country	Germany	France
Provider	Volksbanken Raiffeisenbanken	La Banque Postale
Description	This is a growth product linked to the performance of the DJ Eurostoxx50. The product offers [*100% capital guarantee at maturity*]$^{(1)}$ along with a [*predetermined participation in the rise of the underlying*]$^{(1)}$ over the investment period *[...]*$^{(x)}$: Text identifying Payoff x	This is a growth product linked to a basket of 18 shares selected as being the largest companies by market capitalization from within the eurostoxx50 at the time the product was launched. Every year, the average performance of [*the three best-performing shares*]$^{(2)}$ in the basket compared to their initial levels is recorded. These three shares [*are then removed*]$^{(2)}$ from the basket. At maturity, the product offers [*a minimum capital return of 100%, plus 70% of the average of these performances*]$^{(1)}$ [*recorded annually throughout the investment period*]$^{(3)}$.
Payoff Features	Call	Call - Himalaya - Asian Option
Complexity Measures		
Nb Payoffs	1	3
Nb Scenarios	1	1
Length	226	537

This table displays two real-life examples of product description, and shows how we convert these text descriptions into quantitative measures of complexity.

Table 5. Increasing Complexity

	Nb Payoffs		Nb Scenarios	Length
	(1)	**(2)**	**(3)**	**(4)**
Specification 1				
Year Trend	0.057***	0.053***	0.059***	14.71***
	(0.015)	(0.011)	(0.013)	(3.16)
Specification 2				
2003	0.078	0.161	0.180	10.43
	(0.088)	(0.097)	(0.047)	(9.50)
2004	0.049	0.103	0.172	29.58
	(0.089)	(0.096)	(0.039)	(8.54)
2005	0.121	0.105	0.275	56.67
	(0.106)	(0.114)	(0.051)	(11.17)
2006	0.271	0.294	0.371	87.33
	(0.100)	(0.087)	(0.064)	(12.83)
2007	0.292	0.342	0.426	103.09
	(0.094)	(0.086)	(0.061)	(12.41)
2008	0.337	0.380	0.366	100.36
	(0.088)	(0.084)	(0.060)	(12.52)
2009	0.378	0.384	0.451	110.42
	(0.111)	(0.083)	(0.076)	(17.22)
2010	0.453	0.434	0.613	129.34
	(0.106)	(0.084)	(0.072)	(15.45)
Underlying FE	Yes	Yes	Yes	Yes
Distributor FE	Yes	Yes	Yes	Yes
Product Format FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Volume Weight	No	Yes	No	No
Maturity	Yes	Yes	Yes	Yes
Observations	54,716	52,478	54,716	54,716

This table displays the coefficient of OLS regressions in which the dependent variables are our complexity measures, i.e. the number of pay-offs, the number of scenarios, and the length of the descriptive. The explanatory variables are respectively a year linear trend and year dummies in first and second specification. Number of payoffs features is obtained through a lexicographic analysis of the detailed pay-off descriptives. Number of scenarios is constructed by counting the number of conditions in the product descriptives. Length is the number of characters of the payoff descriptives. Standard errors are clustered at the distributor level. Data is from Euromoney SRP.

Table 6. Complexity Measures and Financial Sophistication

	Nb Payoffs (1)	Nb Scenarios (2)	Description Length (3)
Summary Statistics			
Savings Bank			
Mean	2.7	2.7	533
Standard Deviation	1.1	1.6	227
Max	8	16	2,595
Private Banking			
Mean	2.5	2.2	503.9
Standard Deviation	1.1	1.5	213
Max	7	9	2,102
Commercial Bank			
Mean	2.3	2.0	472.8
Standard Deviation	1.1	1.4	206
Max	7	11	2,203
Other			
Mean	2.5	2.2	503.9
Standard Deviation	1.1	1.5	213
Max	7	9	2,102
OLS Estimation			
Savings Bank	0.168**	0.217**	46.840**
	(0.082)	(0.103)	(23.375)
Private Bank	0.126*	-0.014	4.537
	(0.068)	(0.085)	(12.543)
Controls			
Underlying FE	Yes	Yes	Yes
Product format FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Volume	Yes	Yes	Yes
Maturity	Yes	Yes	Yes
Observations	54,716	52,416	54,716

The upper half of the table displays summary statistics of our three measures of complexity by distributor type. The bottom half of the table displays OLS regressions in which the dependent variables are our three measures of complexity. The explanatory variables are dummy variables indicating the type of the distributor. Number of payoff features is obtained through a lexicographic analysis of the detailed pay-off descriptive. Number of scenarios is constructed by counting the number of conditions in the product descriptive. Length is the number of characters of the payoff descriptive. Data is from Euromoney Structured Retail Products.

Table 7. Product Complexity and Profitability

	Product Yearly Markup, in %					
					Disclosed Fees Incl.	**PDE Pricing**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Nb Payoffs	0.28***	0.32**	0.27***	0.27*	0.43***	0.28*
	(0.08)	(0.14)	(0.08)	(0.13)	(0.15)	(0.16)
Credit Risk Dummy	-0.66**	-0.91	-0.61*	-0.69**	-2.49***	-0.10
	(0.29)	(1.03)	(0.32)	(0.29)	(0.41)	(0.28)
Controls						
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Distributor FE	-	Yes	-	-	-	-
Main Feature FE	-	-	Yes	Yes	-	-
Facultative Feature FE (Main)	-	-	-	Yes	-	-
Observations	101	101	101	101	101	71
R^2	0.240	0.547	0.332	0.402	0.458	0.078

This table displays coefficients of OLS regressions, in which the dependent variable is the yearly markup in percent of product notional for all the products indexed to the Eurostoxx 50 sold in Europe in July 2009 (101 products). Markups are computed as the difference between the offering price and the product calculated fair value, which we obtain by using Longstaff and Schwartz OLS MonteCarlo pricing methodology (Longstaff and Schwartz (2001)) with a local volatility diffusion. Volatility surface data is from Eurex. The explanatory variable is the number of payoff features. Control variables include country fixed effects, distributor fixed effects, as well as main and facultative feature fixed effect. Standard errors are clustered at the distributor group level (30 clusters), and reported into brackets.

Table 8. Product Complexity and Ex-post Performance

	Product Yearly Return, in %					
	All	**ESTX50**	**All**	**ESTX50**	**All**	**ESTX50**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Nb Payoffs	-0.290*	-0.273				
	(0.175)	(0.362)				
Nb Scenarios			-0.444**	-0.207		
			(0.212)	(0.228)		
Description					-0.002**	-0.003
Length					(0.001)	(0.003)
Controls						
Country FE	Yes	-	Yes	-	Yes	-
Distributor FE	-	Yes	-	Yes	-	Yes
Underlying FE	Yes	-	Yes	-	Yes	-
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Credit Risk Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Capital Protection FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,467	968	7,467	968	7,467	968
R^2	0.415	0.209	0.417	0.211	0.417	0.216

This table displays coefficients of OLS regressions, in which the dependent variable is the yearly rate of return for growth products that have reached their term. Growth products only have one final pay-off. Columns (2), (4) and (6) restrict the sample on products indexed to the Eurostoxx 50. The explanatory variables are our complexity measures: number of pay-off features (columns (1) and (2)), number of scenarios (columns (3) and (4)), and the length of the pay-off description (columns (5) and (6)). Control variables include country, year, distributor, underlying asset, and capital protection fixed effects and a credit risk dummy for products that are non-collateralized. Standard errors are clustered at the distributor level, and reported into brackets. Performance data is from Euromoney SRP.

Table 9. The Impact of ETF Introduction on Complexity

Panel A	Country Level				
	Nb Payoffs			**Nb Payoffs** (> 1)	
	(1)	(2)	(3)	(4)	(5)
ETF entry $\times$ Year $\geq t$	0.279***	0.305***		0.251***	
	(0.087)	(0.092)		(0.087)	
ETF entry $\times$ Year $= t-1$			-0.045		0.012
			(0.107)		(0.083)
ETF entry $\times$ Year $= t$			0.146		0.177
			(0.117)		(0.115)
ETF entry $\times$ Year $> t$			0.331**		0.421***
			(0.166)		(0.157)
Controls					
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Banking Sector Profitability	-	Yes	-	-	-
Observations	112	83	105	112	105
R^2	0.650	0.725	0.669	0.457	0.493

Panel B	Distributor Level				
	Nb Payoffs				
	(1)	(2)	(3)	(4)	(5)
ETF entry $\times$ Year $\geq t$	0.108***	0.095***		0.032	
	(0.018)	(0.022)		(0.036)	
ETF entry $\times$ Year $= t-1$			-0.010		-0.009
			(0.023)		(0.044)
ETF entry $\times$ Year $= t$			0.078***		0.008
			(0.028)		(0.053)
ETF entry $\times$ Year $> t$			0.277***		0.165**
			(0.039)		(0.077)
Controls					
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Distributor FE	Yes	Yes	Yes	Yes	Yes
Distributor-Year FE	-	-	-	Yes	Yes
Issued Volumes	Yes	Yes	Yes	Yes	Yes
Banking Sector Profitability	-	Yes	-	-	-
Observations	2,479	1,639	2,479	2,479	2,479
R^2	0.809	0.838	0.821	0.930	0.933

This table displays coefficient of OLS regressions on unbalanced panel data at the distributor-country level over the period 2002-2010. All countries are included except Norway over the 2008-2010 period due to a ban on structured products, and Hungary and Poland due to insufficient volumes. The dependent variable is the average complexity of products for a given distributor in a given country and for a given year. The difference-in-differences methodology is based on the staggered entries of ETF across European countries. ETF is a dummy which is equal to one once ETFs have been introduced in a given country, as measured by the appearance of the keyword "ETF" in Google Trend. Standard errors are clustered at the distributor level, and reported into brackets.

Table 10. Competition and Complexity

Panel A	**Country Level**				**Distributor Level**	
	Nb Payoffs		**Nb Types**		**Nb Payoffs**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Nb Competitors	0.012**	0.019**	2.338***	4.139***	0.009*	0.016***
	(0.005)	(0.009)	(0.818)	(0.789)	(0.005)	(0.006)
Controls						
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Distributor FE	-	-	-	-	Yes	Yes
Banking Sector Profitability	-	Yes	-	Yes	-	Yes
Observations	132	101	132	101	2,507	1,682
R^2	0.553	0.578	0.812	0.854	0.444	0.462

Panel B	**Country Level**				**Distributor Level**	
	Nb Payoffs (Change)		**Nb Types (Change)**		**Nb Payoffs (Change)**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Δ Nb Competitors	-0.001	-0.008	1.499***	2.072***	0.010**	0.010*
	(0.004)	(0.007)	(0.558)	(0.525)	(0.005)	(0.006)
Controls						
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Banking Sector Profitability	-	Yes	-	Yes	-	Yes
Observations	117	88	117	88	1,822	1,183
R^2	0.001	0.017	0.204	0.382	0.005	0.009

This table displays coefficient of OLS regressions on unbalanced panel data at the country and distributor level over the period 2002-2010. All countries are included except Norway over the 2008-2010 period due to a ban on structured products, and Hungary and Poland due to low representativeness. Volume sold since inception has been lower than 10 million euros in these countries standing for less than 2% of financial savings. In panel A, the dependent variable is the average complexity of products, measured at the country x year level for columns 1 and 2, and at the distributor level for column 4 and 5. The dependent variable of column 3 is the number of product varieties offered in a country a given year. The explanatory variable for all columns is the number of competitors in the retail market for structured products at the country x year level. In panel B, the dependent variables are the yearly absolute change of the previously described variables. Banking sector profitability represents the aggregate amount of profit by bank in a given country and a given year. Standard errors are robust to heteroskedasticity in columns 1 to 3, and clustered at the distributor level in columns 4 and 5, and reported into brackets.

Appendix A - Retail Structured Product Typology

Product Underlying

Asset Name	*Description (in frequency order)*
Equity (Single Index)	Eurostoxx50, FTSE100, SP500, DAX, Ibex35, OMSX30, Nikkei225, CAC40, BRIC40
Equity (Single Stock)	Deutsche Bank, Credit Suisse, Daimler, Zurich Finance, Roche, Abb, BASF, UBS, Siemens, Allianz, Nestle
Commodity	Gold, brent, electricity, silver, corn
Foreign Exchange	Euro/USD, PLN/Euro, CSK/Euro, CHF/Euro
Credit Default	The risk of default of a company or a country
Interest Rates	Euribor, Libor, Swap rate
Other	Inflation, Funds

Main Feature (Primary Structure)

Structure Name	*Definition*
Altiplano	The product offers a capital return of 100%, plus a series of fixed coupons on each sub periods if the underlying is above a predefined barrier.
Floater	The product offers a capital return of 100% plus a series of coupons that rise when the underlying reference rate rises.
Pure Income	The product offers a capital return of 100% plus a series of fixed coupons.
Digital	The product offers a capital return of 100%, plus a fixed coupon paid at maturity if the underlying is above a predefined barrier.
Call	The product offers a capital return of 100% plus a fixed participation in the rise of the underlying.
Put	The product offers a capital return of 100% plus a fixed participation in the absolute value of the fall of the underlying.
Spread	The product offers a capital return of 100% plus a participation related to the spread between the performances of different underlyings (shares, rates.).
Bull Bear	The final return is based on a percentage of the absolute performance of the underlying at maturity.

Feature Type 1: Initial Subsidy (facultative)

Feature Name	*Definition*
Discount	
Guaranteed Rate	
Bonus	

Feature Type 2: Underlying Selection (facultative)

Feature Name	*Definition*
Best of Option	The return is based on the performance of the best performing underlying assets.
Worst of Option	The return is based on the participation in the performance of the worst performing underlying assets.
Himalaya	A pre-selected number of best-performing assets are permanently removed from the basket, or frozen at their performance level, at the end of each period until the end of the investment.
Kilimanjaro	The lowest performing assets as well as the best performing assets have been progressively eliminated, or ignored from subsequent calculations, during the investment period.
Rainbow	Best performing assets are weighted more heavily than those which perform less well.

Feature Type 3: Exposure Modulation, Increased Downside (facultative)

Feature Name	*Definition*
Reverse Convertible	The product is capital guaranteed unless a performance criterion is not satisfied. In this case, the capital return is reduced by the percentage fall in the underlying, or the product pays back a predefined number of shares/bonds.
Precipice	The product is capital guaranteed unless a performance criterion is not satisfied.

Feature Type 4: Exposure Modulation, Limited Upside (facultative)

Feature Name	*Definition*
Cap	The return is based on the participation in the performance of the worst performing underlying assets.
Fixed Upside	The best performances of a basket of stocks or of a set of subperiod returns are replaced by a predetermined fixed return.
Flip Flop	The coupons are fixed in the first periods, and the distributor has the right to switch you into floating.

Feature Type 5: Path Dependence (facultative)

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

Feature Type 6: Exotic Condition (facultative)

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

Feature Type 7: Early Redemption (facultative)

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

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

Appendix B - Figures

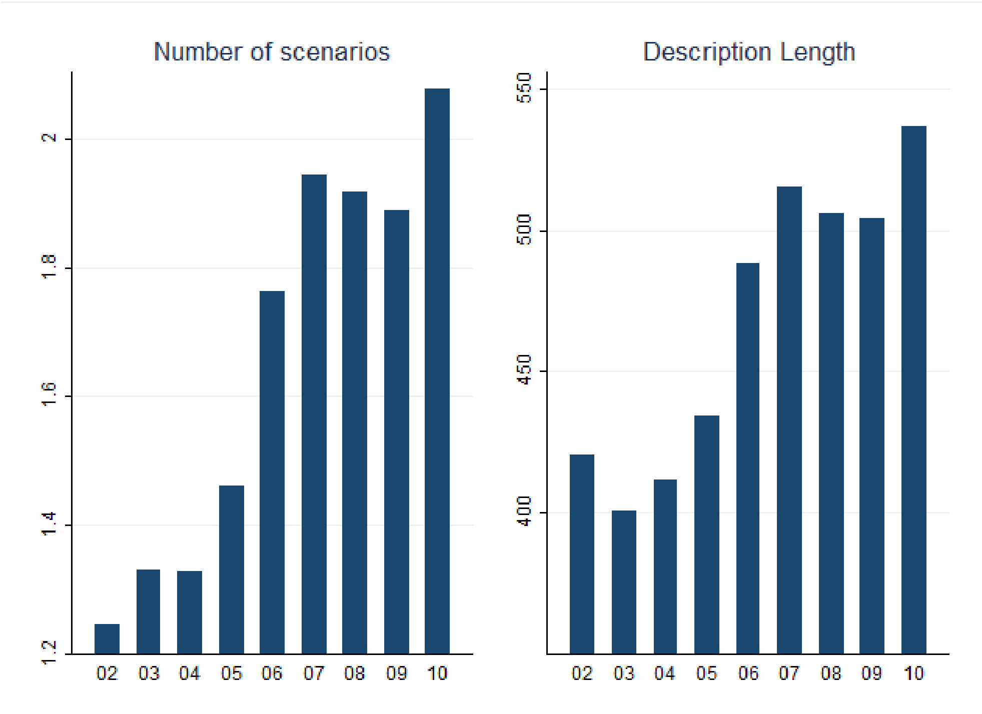

Figure B.0. Average Product Complexity by Year

This figure shows the average of our robustness checks proxies for complexity by year. *Number of Scenarios* measures the number of conditions embedded in the final payoff formula, and *Description Length* the number of characters in the standardized text description of the payoff formula.

Appendix C - Tables

Table C.1. The 20 Main Distributors in terms of Market Share in 2010

Name	Country of Origin	Market Share in %	N. of Payoffs	Type	Distribution Countries
Deutsche Volks & Raiffeisenb.	DE	11.6	2.8	Savings B	AT DE IT PL
Deutsche Sparkassen	DE	10.6	2.7	Savings B	AT CZ DE
Deutsche Bank	DE	4.8	3.2	Commercial B	AT BE DE IT NL PL PT ES UK
UBS	CH	4.1	2.3	Private B	AT BE FR DE IT NL NO ES
RBS	UK	3.9	2.1	Commercial B	AT BE DK FI FR DE IE IT NL PT ES SE UK
KBC	BE	2.8	2.8	Commercial B	BE CZ FR HU IE NL PL UK
Santander	ES	2.7	2.4	Commercial B	PL PT ES UK
Unicredit	IT	2.7	2.7	Commercial B	AT CZ DE HU IT PL ES
Commerzbank	DE	2.5	2.8	Commercial B	AT BE FR DE HU IT NL NO PL ES
Barclays	UK	2.5	2.5	Commercial B	AT BE CZ FR DE IE IT NL PT ES UK
Bnp Paribas	FR	2.4	3.1	Commercial B	AT BE FR DE HU IT NL PL PT ES UK
Nordea	SE	2.3	2.0	Commercial B	DK FI IT NO PL SE
Garantum	FI	2.1	3.5	Private B	FI SE
Societe Generale	FR	2.1	3.2	Commercial B	AT BE CZ FR DE IT NL PL ES UK
Caja De Ahorros	ES	2.0	2.1	Savings B	PT ES
Investec	ZA	1.9	2.5	Private B	IE UK
Seb	SE	1.4	2.1	Commercial B	DK FI DE NO PL SE
Osterreichische Volksbanken	AU	1.4	1.5	Commercial B	AT DE HU
ING	NL	1.4	2.7	Commercial B	AT BE CZ FR DE IT NL PL ES UK
Jp Morgan	US	1.1	3.2	Private B	AT BE FR DE IT NL PL ES UK

Market shares are computed in terms of number of product issued in Europe in 2010. Countries of distribution are idicated with their ISO 3166 code

Table C.2. Details of the retail structured product issued in July 2009 (1/4)

Product Name	**Provider Name**	**Country**	**Credit Risk**	**Maturity** in years	Number Payoffs	Markup in %	**Entry fees** in %	Mana. fees in %
Sprint Zertifikat	Hypovereinsbank	Germany	yes	4.4	1	-8.0	2.0	0.0
Summer Invest	Allianz Belgium	Belgium	no	4.9	1	-4.6	4.0	0.0
Phoenix 2	Bank of Scotland	Ireland	no	3.9	2	-3.6	3.5	0.0
Europa Anleihe 10% Plus Ii 08/09 - 08/14	Barclays	Austria	yes	5	2	-3.6	5.0	0.0
Europa Anleihe 10% Plus 07/09-07/14	Barclays	Austria	yes	5	2	-3.5	5.0	0.0
Eurostoxx 50 Zins Anleihe 4	Barclays	Austria	yes	5	2	-2.9	2.5	0.0
4Y Eur Market Recovery Note	ING	Belgium	yes	4	1	-2.4	0.0	0.0
Eurozone Coupon Note	Ing Bank	Netherlands	yes	5	2	-2.0	0.0	0.0
Dz Bank Vr Garantieanleihe 09/14	Dz Bank	Germany	yes	5	2	-1.9	2.0	0.0
3Y Market Recovery Note	ING	Belgium	yes	3	1	-1.7	0.0	0.0
Europa Kupon Anleihe	Landesbank Berlin	Germany	yes	5	1	-1.4	0.0	0.0
Seguro Rentabilidad Eurostoxx 114 Db	Deutsche Bank	Spain	no	3.4	2	-1.1	0.0	1.4
Barrier Note Dj Eurostoxx50	ING	Belgium	yes	1.5	2	-1.1	0.0	0.0
Seguro Rentabilidad Eurostoxx 119 Db	Deutsche Bank	Spain	no	3.9	2	-1.1	0.0	1.4
Cs Garant 100 Anleihe 13 Dj Euro Stoxx 50	Credit Suisse	Austria	yes	5	2	-1.1	2.0	0.0
Europa Protect-Anleihe 07/09	West Lb	Germany	yes	4	3	-1.1	2.0	0.0
Seguro Rentabilidad Eurostoxx 122 Db	Deutsche Bank	Spain	no	4.4	2	-0.9	0.0	1.2
Euro Booster 200%	Swiss Life Banque Privee	France	yes	5	4	-0.9	0.0	0.0
Europa-Anleihe	Landesbank Berlin	Germany	yes	5	2	-0.8	0.0	0.0
Seguro Rentabilidad Eurostoxx 110 Db	Deutsche Bank	Spain	no	2.9	2	-0.7	0.0	1.0
Cs Top Bonus 115 200	Credit Suisse	Austria	yes	5	2	-0.7	3.5	0.0
Partizipationsanleihe 01/09	Nordlb	Germany	yes	4	2	-0.4	0.0	0.0
Cp100 Cap-Performanceanleihe	Sal. Oppenheim	Austria	yes	4	2	-0.4	1.5	0.0
Vital Ibex Bolsa Garantizado	Caja Vital Kutxa	Spain	no	2.5	2	-0.3	5.0	5.6
Lbbw Safe-Anleihe Mit Cap	Landesbank Bw	Germany	yes	4	2	-0.3	1.0	0.0

Table C.3. Details of the retail structured product issued in July 2009 (2/4)

Product Name	**Provider Name**	**Country**	**Credit Risk**	**Maturity** in years	Number Payoffs	Markup in %	**Entry fees** in %	Mana. fees in %
Igc Dj Eurostoxx50 - Juli 2009	Van Lanschot Bankiers	Netherlands	no	5	2	-0.1	2.0	3.3
Europa-Anleihe	Landesbank Berlin	Germany	yes	5	2	-0.0	2.0	0.0
Dj Eurostoxx50 Partizipations-Anleihe	Landesbank Berlin	Germany	yes	5	3	0.2	1.5	0.0
Objectif 7.5% Juin 2009	Swiss Life Banque Privee	France	yes	8	4	0.3	0.0	0.0
Easy Bonus-Zertifikat	West Lb	Germany	yes	4.3	2	0.3	1.0	0.0
Equity Protection Switchable	Deutsche Bank	Italy	yes	5	2	0.5	3.3	0.0
Objectif 7,5% Distribution Juillet 2009	Swiss Life Banque Privee	France	yes	8	4	0.6	0.0	0.0
Bs Garantia Extra 10	Banco Sabadell	Spain	no	3.1	3	0.8	5.0	3.0
Europa Protect-Anleihe Extra 03/09	West Lb	Germany	yes	6	2	0.8	2.5	0.0
Vr Extrachance Ii	Dz Bank	Germany	yes	4.4	2	1.0	3.0	0.0
Bbva Oportunidad Europa Bp	Bbva	Spain	no	2.9	2	1.1	5.0	6.8
Euro Booster	Swiss Life Banque Privee	France	yes	5	4	1.2	0.0	0.0
Ten Pea	Barclays	France	no	1	6	1.2	2.0	3.0
Dz Bank Bonuschance Control 3 09/13	Dz Bank	Germany	yes	3.5	2	1.4	0.0	0.0
Dz Bank Bonuschance Control Iii 09/13	Dz Bank	Austria	yes	3.5	2	1.4	0.0	0.0
Athena 11% Airbag	Swiss Life Banque Privee	France	yes	8	4	1.4	0.0	0.0
Bonus Pro Zertifikat	Hypovereinsbank	Germany	yes	4.4	1	1.5	2.0	0.0
Best-Entry Garant V-Anleihe	Bayerische Landesbank	Germany	yes	4.5	2	1.6	1.0	0.0
Europa Protect Anleihe Plus	Jpmorgan Chase	Germany	yes	6	2	1.6	2.0	0.0
Bbva Europa Garantizado	Bbva	Spain	no	2.9	3	1.7	5.0	3.6
Kbc-Life Mi Security Europe 2	Kbc Verzekeringen / Cbc Assurance	Belgium	no	7.6	2	1.8	3.0	18.2
Callable Booster Notes	Barclays	Belgium	yes	6	3	1.9	0.0	0.0
Eurostoxx Serenite 2009	Credit Suisse	France	no	6	2	2.0	3.0	12.0
Deposito Imbatible 8-5	Bbk	Spain	no	3.4	4	2.1	0.0	0.0
Rentenbank Capped Capital Protected Note	Abn Amro Bank	Netherlands	yes	7	2	2.1	0.0	0.0

Table C.4. Details of the retail structured product issued in July 2009 (3/4)

Product Name	**Provider Name**	**Country**	**Credit Risk**	**Maturity** in years	Number Payoffs	Markup in %	**Entry fees** in %	Mana. fees in %
Dz Bank Indexklassik Garant 5 09/13	Dz Bank	Germany	yes	4.4	2	2.1	2.5	0.0
Dz Bank Indexklassik Garant V 09/13	Dz Bank	Austria	yes	4.4	2	2.1	2.5	0.0
Dj Eurostoxx 50 Bonus Minimax	Landesbank Berlin	Germany	yes	3	3	2.4	0.5	0.0
Express Zertifikat	Deutsche Bank	Austria	yes	2	4	2.4	1.0	0.0
Mes-Rendements 10%	Finance Selection	France	yes	5	5	2.6	0.0	0.0
Europa Callable Protect Anleihe	Jpmorgan Chase	Germany	yes	5	4	2.6	1.5	0.0
Cs Memory Express Zertifikat 6	Credit Suisse	Germany	yes	6	5	2.6	2.5	0.0
Autofocus 9%	Credit Mutuel Arkea	France	no	5	3	2.6	2.0	3.5
Europa Garant Plus-Anleihe	Landesbank Berlin	Germany	yes	6	2	2.7	1.0	3.0
Btv Europa Bonus Garantieanleihe Plus Iii 2009 - 2014/12	Btv Bank	Austria	yes	5.5	4	2.7	0.0	0.0
Dexia Clickinvest B Index Linked 7	Dexia Bank	Belgium	no	5.1	2	2.8	2.5	11.9
Cs Top Bonus Chance 3	Credit Suisse	Germany	yes	4.4	2	2.8	1.5	0.0
Eurostoxx 50 Flex-Express 02/09	West Lb	Germany	yes	3	1	3.0	1.0	0.0
Cs Top Memory Express	Credit Suisse	Germany	yes	4	6	3.1	1.0	0.0
Switch To Bond Note	Fortis	Belgium	yes	5	4	3.1	0.0	0.0
Indexanleihe	Nordlb	Germany	yes	1	2	3.1	0.0	0.0
Dexia Clickinvest B Index Linked 8	Dexia Bank	Belgium	no	5.1	2	3.3	2.5	11.9
Unigarant: Europa (2015)	Union Investment	Germany	no	5.9	2	3.3	4.0	6.0
Kbc Clickplus Europe Best Of 42	Kbc Bank	Belgium	no	8.6	3	3.8	2.5	19.1
Centea Fund Click Europe Surplus 10	Centea	Belgium	no	8.6	3	3.8	2.5	17.0
Zanonia-Deep-Zertifikat	Landesbank Bw	Germany	yes	4	3	3.8	1.0	0.0
Buono Fruttifero Postale 16D	Bancoposta	Italy	yes	5	2	3.9	0.0	0.0
Eurostoxx Fast 7%	Swiss Life Banque Privee	France	yes	8	4	4.0	0.0	0.0
Dz Bank Extrachance Pro V 09/13	Dz Bank	Austria	yes	4	2	4.3	2.3	0.0
Dz Bank Extrachance Pro 5 09/13	Dz Bank	Germany	yes	4	2	4.3	2.3	0.0

Table C.5. Details of the retail structured product issued in July 2009 (4/4)

Product Name	**Provider Name**	**Country**	**Credit Risk**	**Maturity** in years	Number Payoffs	Markup in %	**Entry fees** in %	Mana. fees in %
Dz Bank Vr Extrachance Iii 09/13	Dz Bank	Germany	yes	4	2	4.3	2.3	0.0
Express Zertifikat	Hypovereinsbank	Germany	yes	2	4	4.4	0.5	0.0
Bono Autocancelable 8% Cupon	Citi	Spain	yes	5	3	4.4	3.0	0.0
Wgz Garant-Zertifikat 22	Wgz Bank	Germany	yes	6	2	4.5	2.0	0.0
Emtn Memory Express-Zertifikat 4	Societe Generale	Germany	yes	6	5	4.7	2.0	0.0
Bonus Control Iv	Dz Bank	Austria	yes	4	2	4.8	2.5	0.0
Seguro Recuperacion Eurostoxx Db	Deutsche Bank	Spain	no	3	1	5.3	0.0	1.0
Bankinter Eurostoxx 2012 Garantizado	Bankinter	Spain	no	3	3	5.4	5.0	6.8
Euro Memory	Nortia	France	yes	8	5	5.5	0.0	0.0
Reference 8,5%	Adequity	France	no	8	4	5.5	4.5	2.0
Optimiz 7%	Societe Generale	Italy	yes	8.2	2	5.6	0.0	0.0
Step Dj Eurostoxx 50	Banca Aletti	Italy	yes	3	3	5.8	0.0	0.0
Phoenix Memory	Adequity	Belgium	yes	4	5	5.8	0.0	0.0
Zanonia-Plus-Zertifikat	Landesbank Bw	Germany	yes	4	4	6.0	1.0	0.0
Wgz Airbag-Zertifikat Mit Cap	Wgz Bank	Germany	yes	5	4	6.6	2.0	0.0
Wgz Easyexpress-Zertifikat 12	Wgz Bank	Germany	yes	4	2	6.6	2.0	0.0
Buono Fruttifero Postale P22	Bancoposta	Italy	yes	5	2	7.2	0.0	0.0
Fortis B Fix 2009 Best Of Click 6	Bnp Paribas Fortis	Belgium	no	8.5	3	7.9	2.5	0.0
Elixis 2	Credit Agricole	France	no	4.2	4	8.1	2.0	10.0
Cap Garanti 2015	Credit Mutuel	France	no	5.9	2	8.1	3.0	2.5
Sevea	Gestion Privee Indosuez	France	no	5	4	8.8	2.5	12.5
Ing (L) Selectis Euro Equity 1	Ing Luxembourg	Belgium	no	4.5	3	9.2	3.0	6.8
Bif Certi+ 200	Alternea	Belgium	no	6	3	9.4	5.0	7.2
Oriance Epargne 2	Credit Agricole	France	no	6.8	2	11.8	0.0	0.0
Euro Cap 2017 (EUro Cap 2017)	Hsbc Assurances Vie	France	no	6	3	11.9	0.0	0.0
Recovery Note	Abn Amro Bank	Netherlands	yes	5	3	14.8	0.0	0.0

Appendix D - Theoretical Framework (Model)

We develop a model in which firms strategically use financial complexity to mitigate competition. The model is inspired by Carlin (2009), but differs in that consumers are heterogeneously distributed across firms and may face switching costs. For tractability purposes, the fraction of uninformed consumers is taken as exogenous.

Model Setup

Consumers

Consider a market in which n firms produce a homogeneous retail financial product. In this market, there is a unit mass of consumers M who each has a unit demand for the retail good. Each consumer i maximizes the same utility function

$$U_i = v - p_i$$

where v is the fundamental value of the product and p_i its price.

Firms

Firms in this market face the same marginal production cost, which is fixed at zero, but differ in the structure and level of the price that they charge. They can sell the financial product either in a *simple* price structure, thereafter the "package", or in a *complex* one, implying no additive cost. In the complex price structure, the price of the product is not observable by consumers.

Firms also differ in the fraction of consumers in their neighbor. A firm of rank j captures a fraction α_j of consumers, with $0 \leq \alpha_j \leq 1$, $\alpha_{j+1} < \alpha_j$ and $\sum_1^n \alpha_j = 1$.

To simplify the analysis, we restrict the firms to choose prices in the interval $[p; P]$, with $p > 0$ and $P = v$ is the monopoly price.

Financial Sophistication

Consumers are divided into two groups: a fraction μ is uninformed, and a fraction $1 - \mu$ is expert. Expert consumers are knowledgeable about the price structure of a product and face no switching cost. They consequently only buy simple products, whose prices they can observe, at the lowest price available. In contrast, uninformed consumers are uneducated about prices even for a simple package, and face a switching cost $c > 0$. As a result, uninformed consumers purchase the retail financial product from the firm they are already on relationship with, independently of the price package.

Timing

The game is in two periods. In stage one, firms simultaneously set prices and decide if the price structure is going to be complex or simple. In stage two, consumers buy the product with a strategy based on their type.

Results

Consider the price of a simple product. There is free entry of firms. New entrants capture a fraction $\alpha = 0$ of consumers. Free entry implies that the price of a simply structured product is the minimum price, p. If a firm j decides to sell the product with the simple price structure, it receives a fraction $1/n_s$ of the demand from experts - n_s denoting the number of firms with the same strategy - plus the demand from the fraction α_j of captured uninformed consumers. Its profit is

$$\Pi_{j,s} = p\big(\frac{\mu}{n_s} + \alpha_j(1-\mu)\big)$$

Consider now the price of a complex product. By selling the product in the complex package, a firm will receive demand only from uninformed consumers who do not observe prices. It is optimal in this case to sell the product at a maximum price P. The payoff of a firm selling the complex product is

$$\Pi_{j,c} = \alpha_j(1-\mu)P$$

Firm j sells the product in a complex package if and only if

$$\begin{aligned} \Pi_{j,c} &\geq \Pi_{j,s} \\ \Leftrightarrow \alpha_j(1-\mu)P &\geq p\big(\frac{\mu}{n_s} + \alpha_j(1-\mu)\big) \\ \Leftrightarrow \alpha_j &\geq \frac{p\mu}{P(1-p)(1-\mu)} * \frac{1}{n_s} \\ \Leftrightarrow \alpha_j &\geq \frac{A}{n_s} \end{aligned}$$

with $A = \frac{p\mu}{P(1-p)(1-\mu)}$ This leads to the following proposition

Proposition 1 *The tendency of a firm to sell a complex product increases with the share of uninformed consumers it is initially in a relationship with.*

We make the following assumption

Assumption 1

$$\alpha_1 > \frac{A}{n}$$

Assumption 1 implies that it is optimal for the firm of rank 1, namely the one with the biggest market share, to sell the product in the complex package if all other firms in the market choose to sell the simple product.

Lemma 1 *There exists a unique* $\overline{k}$ *such that:*

- *Firms of rank* j*, with* $1 \leq j \leq \overline{k}$*, choose to sell the product in the complex package*
- *Firms of rank* j*, with* $\overline{k} < j \leq n$*, choose to sell the product in the simple package*

Proof.

Let denote f the function defined by:

$$f(k) = \alpha_k - \frac{A}{n-k+1}$$

By definition, α_k is a decreasing function of k, and $-\frac{A}{n-k+1}$ is also decreasing in k. In addition, Assumption 1 implies that $f(1) > 0$ and $f(n) < 0$. Therefore, there exists a unique $\overline{k}$ such that for any $j \geq \overline{k}$ we have $f(j) \geq 0$ whereas for any $j < \overline{k}$ we have $f(j) \leq 0$. ■

Let $\phi(n)$ define the fraction of complex products as a function of the number of competitors. We have

$$\phi(n) = \frac{\overline{k}}{n}$$

Now we make the assumption that we are in a *neck-and-neck* market, in which the distance between two firms, measured by the difference in market share α, is small. It implies

Assumption 2

$$\alpha_{\overline{k}} - \alpha_{\overline{k}+1} < \frac{A}{n-\overline{k}} - \frac{A}{n-\overline{k}+1}$$

We obtain the following proposition

Proposition 2 *In a neck-and-neck market, as competition increases, the fraction of complex products increases as well (ϕ increases).*

Proof. By assumption, for any new entrant $n+1$ we have $\alpha_{n+1} = 0$. We also have

$$\begin{cases} \alpha_{\overline{k}} \geq \dfrac{A}{n-\overline{k}+1} \\ \alpha_{\overline{k}+1} < \dfrac{A}{n-\overline{k}} \\ \alpha_{\overline{k}+1} < \alpha_{\overline{k}} \end{cases}$$

Since the market is *neck-and-neck* we have also

$$\alpha_{\overline{k}} - \alpha_{\overline{k}+1} < \frac{A}{n-\overline{k}} - \frac{A}{n-\overline{k}+1}$$

implying

$$\frac{A}{n-\overline{k}+1} < \alpha_{\overline{k}+1} < \frac{A}{n-\overline{k}} < \alpha_{\overline{k}}$$

A new entrant will make the firm $\overline{k}+1$ change its strategy and switch to a complex package. The fraction of complex products increases

$$\phi(n+1) = \frac{\overline{k}+1}{n+1}$$

■