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The Complexity and Returns of Structured Products

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Abstract

In this paper we analyze if higher complexity gives lower returns in structured products. Our unique, hand collected sample consists of 499 structured products sold in Sweden that matured or were subject to early redemption during 2016. We assign a complexity score to each product based on the conditions of their payoff profiles. Our sample consists of products with complexity scores 1 through 4 out of a possible 1 to 8. We perform two regressions. In a panel regression, we regress monthly returns on complexity score and find that products of complexity score 3 earn a statistically significant -0.5% lower monthly returns than products of complexity 1. In the second regression, we use monthly returns that are risk-adjusted using a market factor model. The results from this regression show that products of complexity 4 and 3 perform worse than products of complexity 1 by -0.5% and -0.1%, respectively. Complexity 2 performs better by approximately 0.1%. Our results confirm what previous literature has found; that very complex structured products are difficult to value and that higher complexity can be used to hide risks and fees.

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1 Introduction

1.1 Background and history

Structured products, also known as market-linked investments, is a relatively new invention in the world of finance. Structured products lack any general definition, but they can be said to be specialized portfolios of financial instruments that are sold to investors as pre-packaged strategies. The advantage is that they can be created to meet highly specific needs as the universe of available components is near endless; ranging from common stocks, currencies, options, to bonds and more. Structured products also have the benefit of providing an indirect access to derivatives and financial instruments that could otherwise be unavailable. These retail investor products, as we know them today, have their roots in the systematic deregulation of speculative trading in OTC derivatives in the U.S during the 80's and 90's (Stout, 2011). In Sweden, presently, the structured product market is an industry with 129bn SEK outstanding and 16.8bn SEK new issuance in 2016 (The Swedish Structured Investment Product Association, 2017).

There is a demand for structured products even if research has shown that structured products on average yield lower returns than comparable market indices or even the risk free rate (see for example Henderson and Pearson (2011)). Most financial investments carry risk, and every investor has their own needs in terms of diversification, hedging, and risk preferences. This is one of the big advantages of structured products and a possible explanation for why they are in demand despite relatively poor returns; the ability to get a custom, nonlinear exposure. The key to the nonlinearity is the speculative/probability scenario based payoff that is difficult to obtain elsewhere. For example, an *Autocall* product can generate coupons even if the underlying asset does not increase in value or develops somewhat negatively, while also returning the full nominal amount at maturity as long as the underlying has not fallen below a predefined level.

Both institutions and retail investors invest in structured products, but there appears to be a common reasoning for their demand. The most prevalent product types, approximately 80% of products in our sample, have capital protection, meaning that at the end of a product's life cycle the invested nominal amount is returned to the investor in full. This reduction in downside risk attracts loss averse investors but can entail a price premium.

1.2 Product types and distribution

In a broad sense, structured products can be divided into two types: standardized products and tranche products. Standardized products are continuously sold with an investor picked stock or index basket as the underlying asset. They often have lower complexity and sales volumes than tranche products. Tranche products are designed by distributors and offered in batches for a limited time, usually 4-8 weeks. Entrop et al. (2016) compare two continuous products; discount and bonus certificates, and show that increasing complexity even by small measures in these products causes investor's returns to decrease. They use a factor model to risk-adjust returns of the investor portfolios in their sample. We follow that approach to modeling returns in this paper, but we apply the model on tranche products instead of investor portfolios. We choose to focus on tranche products instead of continuous products as they represent the biggest portion of the structured product market (Source: Structured Retail Products) and due to their more varying complexity.

A structured product passes through up to three institutions before the investor may add it to their portfolio: the issuer, the distributor and the financial advisor. The issuer of a structured product is the legal counter party to the investor and is responsible for payments should the product generate cash flows during its life cycle and/or at maturity. The distributor is the creative party behind the design of structured products. Often they will recycle ideas, changing only the underlying assets and conditional levels that define the payoff while keeping the rest of the product design intact. The financial advisor is the sales point for the products to customers. The advisor also provides feedback to the distributor about what kind of products investors are currently demanding. After designing a product the distributor draws up a contract called *final terms* with the issuer that offers the most favorable deal regarding the financial components that are included in the product. The distributor then transforms the legal information in the final terms into marketing material, that is used by financial advisors to entice possible buyers. Frequently, two or all of these three entities might be just one firm, e.g. SEB distributes, issues and markets their own products while Garantum only designs and markets their products, using varying issuers depending on the specific product.

1.3 Marketing conventions

During the offer period for a batch of structured products the investor has a choice to invest in one or several of them. Structured products often have catchy and metaphorical names, e.g. *SPAX Alpha MAX*, *Turbosprinter Asian Tigers*, *Swedish Companies Smart Bonus Combo*, *African Risk Control* and *Trend Total Growth*. It can be difficult for investors to decide which products to choose since there is no clear way of identifying what type of investment the structured product represents only by looking at the name, e.g. a put option always represents a well defined position but there is no general definition of what position a *Turbosprinter* represents or what underlying assets are called the *Asian tigers*. This is especially true when comparing between distributors as they may use the same name for differing strategies, or different names for the same strategy. Reading the final terms for each product reveals the exact payoff formula and other necessary information about the product, but can be difficult to grasp since it is a legal contract. The more digestible marketing material provides most of the same information but is written in a way to advertise the product, with vibrant introductions and examples of best-case scenario returns. Further, there is no clear way to gather unbiased historical performance of structured products. This is partly because of the non-standardized nature of tranche structured products but also because there is no legal obligation for the distributor to publish such information. Investors then only have the cleverly crafted marketing material and, possibly biased, historical information to base their possible investment decisions on. Because of this non-standardization, there is an information asymmetry that increases with product complexity. We hypothesize that this leads to a correlation between higher structured product complexity and lower returns for the investor.

When a tranche product has been purchased the investor can exit the investment in three ways. The product can mature after a set amount of time, be redeemed ahead of maturity due to certain conditions of its payoff profile, or it can be sold back to the distributor. Usually, structured products are marketed to be held until maturity as they represent scenario based investment strategies with unique payoff profiles that are difficult to price and attract investors with a specific set of preferences. This makes the liquidity of these products extremely low. To alleviate this problem the distributor often acts as a liquidity provider for their products until maturity. Typically there is no closed-form valuation formula for structured products, especially the more complex, which in combination with the lack of an active market and the distributor's reluctance to hold the products themselves creates a liquidity premium for structured products. This means that the distributor actively bids on all their outstanding products but at a price that is less than the fair price that an active market would have created. More complex products are more difficult to value which leads us to believe that the liquidity premium is even higher for them.

1.4 Limitations and literature review

This study is limited to structured products in the Swedish market that matured or were redeemed in 2016. We believe a detailed look at a single country of interest is beneficial as market regulation, product design and demand differ between countries. While some baseline regulation regarding transparency and marketing is standardized across the EU, the

Swedish market is largely self-regulated through voluntary adherence to the guidelines of *The Swedish Structured Investment Product Association* (SPIS). Meanwhile in, for example the neighboring Norway, the regulatory body implemented rules in 2008 that severely limit the sales of structured products to non-institutional investors (The Financial Supervisory Authority of Norway, 2008). Other countries such as Belgium have implemented similar limitations (Financial Services and Markets Authority in Belgium, 2011).

Our paper adds to the growing literature on structured products and other complex financial instruments. Some published papers analyze the degree of overpricing in the structured product market and the performance of investor's product portfolios while others search for explanatory factors behind the demand for these products. Célérier and Vallée (2017) look at the structured product market in all of Europe, focusing on the complexity and best-case scenario returns. Using a text analysis algorithm they analyze the trends and determinants of product complexity for products issued between 2002 and 2010. They conclude that product complexity has been increasing steadily over these years and that riskier products have become more popular. Product complexity and best-case scenario returns are also positively correlated which leads to higher markups. More complex products perform worse and the increased markups yield even worse ex post returns. Similar to them, we look at the relationship between complexity and returns but our focus is not on the best-case scenario returns but on historical return series, with a more detailed focus on the Swedish market and using hand collected data.

Entrop et al. (2016) analyze individual investor's realized portfolio returns between 2004 through 2008 in two types of standardized structured products from a single German bank. They find that investors in their sample have negative risk-adjusted returns on average even before transaction costs. On top of this, the returns are even lower for investments in the more complex product due to higher price premiums and worse underlying selection. Stoimenov and Wilkens (2005) investigate if structured products are fairly priced or not. They compare the daily prices of a large number of structured products in Germany with theoretical values based on the prices of options (which have a similar, nonlinear, payoff). Although their findings are not conclusive, they show that more complex products deviate from the theoretical value to a larger extent. They conclude that the premiums on structured products are high in general but that they can be justified because they offer options with very long time-to-maturity and give investors access to exotic payoffs otherwise unavailable to them.

Some research has been done on complexity and its effects on financial markets. Carlin and Manso (2011) create a dynamic model of obfuscation and investor learning, and show that obfuscation increases with the amount of unsophisticated investors in a market. Small education initiatives actually increase the obfuscation while large education initiatives reduce it, albeit at a heavy cost. An alternate solution is instead increased competition among providers of the complex products. Similarly, Sato (2014) creates a theoretical model of transparent assets (plain-vanilla products) versus opaque assets (such as structured products) and finds that opaque assets trade at a premium even when the payoffs are exactly the same. This *opacity price premium* incentivizes providers to transform transparent assets into opaque. Carlin et al. (2013) again look at the trading of complex assets. Through economic experiments they find that complexity creates asymmetry of information which introduces adverse selection in the market. This in turn leads to lower liquidity and efficiency, and higher volatility of prices.

Other authors such as Hens and Rieger (2014), Helberger (2012), Döbeli and Vanini (2010), and Das and Statman (2013) give a behavioral explanation for the demand for structured products. They find that behavioral biases and incorrect beliefs lead to utility gains according to prospect theory even if the demand does not make sense in terms of expected utility. Structured products with capital protection attract investors with mental accounts for poverty avoidance while call option payoffs with high participation rates give chances at lottery like winnings.

1.5 Data and results summary

We hand collect our dataset from the websites of the largest distributors in Sweden. This unique research sample consists of tranche structured products issued in Sweden with maturity or early redemption in 2016, and the issuing dates for these structured products range from 2010 to 2016. We assign each product in our sample with a complexity score based on the number of features that define their payoff. Using monthly excess returns as the dependent variable, we perform a panel regression with complexity score and a set of product level controls as the explanatory variables. We find that products of complexity score 3 earn roughly 0.5% lower returns than products of complexity 1, 2 and 4 in the first regression. We risk-adjust the returns using a factor model and perform another regression where we find that products of complexity 4 earn roughly -0.5% lower returns than products of complexity 1, products of complexity 3 earn roughly -0.1% lower returns and complexity 2 products earn roughly 0.1% higher returns. Since these results do not point to a clearly linear relationship, we perform an extension of each regression model where we transform the complexity into a continuous variable to investigate the nonlinearity.

We confirm our hypothesis that there is a relationship between increasing complexity and lower returns. The relationship does not appear to be linear but rather the effect is there for some jumps in complexity. The nonlinear checks we perform are not entirely conclusive but do confirm the negative relationship.

The rest of the paper proceeds as follows. In Section 2 we explain the method we use for assigning complexity scores to products in our sample. In Section 3 we present our unique, hand collected dataset and how it was gathered. In Section 4 we show the regression models we use and discuss their results. Finally, in Section 5 we provide concluding remarks.

2 Methodology

We follow Célérier and Vallée's (2017) approach to measuring complexity. The payoff of every product has a number of identifiable features that can be grouped into what we call dimensions. The features within each dimension are mutually exclusive and modify the payoff in some unique way that adds another layer of complexity to the product. Table 2.1 shows the dimensions of payoff complexity that we use in this paper. We list and describe all possible features within each dimension. Each product is assigned a primary feature with up to seven optional features meaning that the lowest possible complexity score is one and the highest is eight. E.g. a product with a *Call* primary feature and *Averaging* as optional feature is complexity 2 while a product with a *Floater* primary feature and *Podium*, *Delay* and *Reverse Convertible* as optional features is complexity 4. By reading the payoff profile descriptions in each product's final terms and marketing brochures we can assign them a complexity score using the table of complexity dimensions, using our own judgment.

In some cases, Célérier and Vallée's (2017) feature descriptions do not fit the payoff profiles in our sample. For example, we introduce a new feature, *Reverse flip flop.* The description for *Flip flop* reads *The coupons are fixed in the first periods and the distributor has the right to switch the investment into floating.* A *Reverse flip flop* feature is identical except the coupons start out floating and can be changed to fixed.

To illustrate how the payoff complexity score is assigned to products, we show the payoff descriptions and complexity classifications for two products in Table 2.2. In the description, we highlight the specific keywords and phrases that tell us the product has a certain primary or optional feature, with the specific feature in parenthesis. For each product, the payoff is described using mathematical formulas in the issuer's final term sheet that is handed to the distributor. The distributor then interprets the formulas and creates marketing brochures with a text description. The descriptions for the two products in our example, however, are our interpretations of the product's respective payoff formulas as described in the final terms since the original descriptions are only available in Swedish and the payoff formulas in the final terms are difficult to understand. We also show the diagrams from the marketing material that are the distributor's payoff examples for these two products in Figures 2.1 and 2.2.

Table 2.1: This table shows all possible dimensions that we assign to our products and the mutually exclusive features inherent to each dimension with a description of the features on the right-hand side. Each product has a primary feature and up to seven optional features, i.e. one from each dimension. From Célérier and Vallée (2017) with slight corrections and additions.

Feature name	**Definition**
Dimension 1: Primary Feature	
Altiplano	The product offers a capital return of 100% plus a series of fixed coupons in each subperiod if the underlying is above a predefined threshold.
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 threshold.
Call	The product offers a capital return of 100% plus a fixed participation in the rise of the underlying.
Put	The product offers a capital return of 100% plus a fixed participation in the absolute value of the fall of the underlying
Spread	The product offers a capital return of 100% plus a participation related to the spread between the performances of different underlyings (shares, rates, etc.).
Bull Bear	The final return is based on a percentage of the absolute performance of the underlying at maturity.
Dimension 2: Initial Subsidy	
Discount	The product offers a discount on the purchase of a given underlying, typically a stock or an index.
Guaranteed Rate Bonus	The product offers an unconditional coupon for a given number of periods.
Dimension 3: Underlying Selection	
Best of Option	The return is based on the performance of the best performing underlying assets.
Worst of Option	The return is based on the participation in the performance of the worst performing underlying assets.
Himalaya	A pre-selected number of best-performing assets are permanently removed from the basket, or frozen at their performance level, at the end of each period until the end of the investment.
Kilimanjaro	The lowest and best performing assets are progressively eliminated, or ignored in subsequent calculations, during the investment period.
Rainbow	Best performing assets are weighted more heavily than those that do not perform as well.
Dimension 4: Exposure Modulation, Increased Downside	

Reverse Convertible	The product is capital guaranteed unless a performance criterion is not satisfied, in which case the capital return is reduced by the percentage fall in the underlying or the product pays back a predefined number of shares/bonds.
Precipice	The product is capital guaranteed unless a performance criterion is not satisfied.
Dimension 5: Exposure Modulation, Limited Upside	
Cap	The return is based on a participation in the rise of the underlying but cannot go above a prespecified level.
Fixed Upside	The best performances of a basket of stocks or set of subperiod returns are replaced by a predetermined fixed return.
Flip Flop	The coupons are fixed in the first periods and the distributor has the right to switch the investment into floating.
Reverse Flip Flop	The coupons are floating in the first periods and the distributor has the right to switch the investment into fixed.
Dimension 6: Path Dependence	
Cliquet	The final return is determined by the sum of returns over some pre-set periods.
Asian Option	The final return is determined by the average underlying returns over some pre-set periods.
Parisian Option	The value of the return depends on the number of days in the period in which the conditions are satisfied.
Averaging	The final underlying level is calculated as the average of the last readings over a given period (more than one month).
Delay	Coupons are rolled up and paid only at maturity.
Catch-up	If a coupon is not attributed in a given period because the condition required for the payment is not met, that missed coupon and any subsequently missed coupon will be rolled up and attributed in the next period in which the condition is met.
Lookback	The initial/final underlying level is replaced by the lowest/highest level over the period
Dimension 7: Exotic Condition	
American Option	The conditions must be satisfied over the entire period considered.
Range	The performance of the underlying is within a range.
Target	The sum of the coupon reaches a predefined level.
Moving Strike	The conditional levels are moving.
Bunch	The top barrier/cap concerns each asset, the bottom barrier the entire basket.
Podium	The underlying is a basket and the final returns depend on the number of shares that satisfy the conditions.
Annapurna	The final return is a maximum of a pre-set return or a fixed participation in the underlying.
Dimension 8: Early Redemption	
Knockout	The product matures early if specific conditions are satisfied.
Callable	The issuer can terminate the product on any coupon date.
Puttable	The investor can terminate the product on any coupon date.

Table 2.2: An example of two products that expired in 2016 with a list of their complexity features and a text description of their respective payoff profiles. We highlight the parts of the description that describe a payoff feature.

Name	SEBO3058 Räntekorridor	Double Autocall BRIC 5 (+/-)
Distributor	SEB	Mangold
Primary feature	Floater	Altiplano
Optional features	-	Underlying selection: Worst of option Exotic condition: Target Early redemption: Knockout Exposure modulation: Reverse Convertible
Complexity score	1	5
Total time alive	7 years	5 years
Payoff description	SEBO3058 pays a yearly **coupon, the size of which depends on the STIBOR rate** [Primary feature: *Floater*] (with a minimum coupon of 3% and a maximum of 6%). At maturity, the product pays back 100% of the nominal invested amount.	The payoff for Double Autocall BRIC 5 (+/-) depends on the **performance of the worst underlying asset** [Underlying selection: *Worst of Option*] in a basket of stock indices related to the BRIC countries. **If, on one of the four yearly observation dates, the worst performing asset is above the coupon barrier level (70% of the starting value) the investor receives a coupon of 15%** [Primary feature: *Altiplano*]. **If this happens a second time during the first four years of the product, the product expires and pays out a coupon of 15% plus the nominal investment amount (100%)**[Exotic condition: *Target* and Early redemption: *Knockout*]. If the worst underlying is below the coupon level on an observation date the investor receives no coupon that year but the product does not expire. If the product has not expired at maturity (5 years), and the worst performing underlying is above 70%, the product pays a coupon of 15% and the nominal amount (100%). If the worst performing underlying is between 55% and 69% of the starting value, the product only pays the nominal amount. **If the worst performing underlying is below 55%, the product pays the nominal amount reduced by the fall of the worst underlying** [Exposure modulation: *Reverse Convertible*].

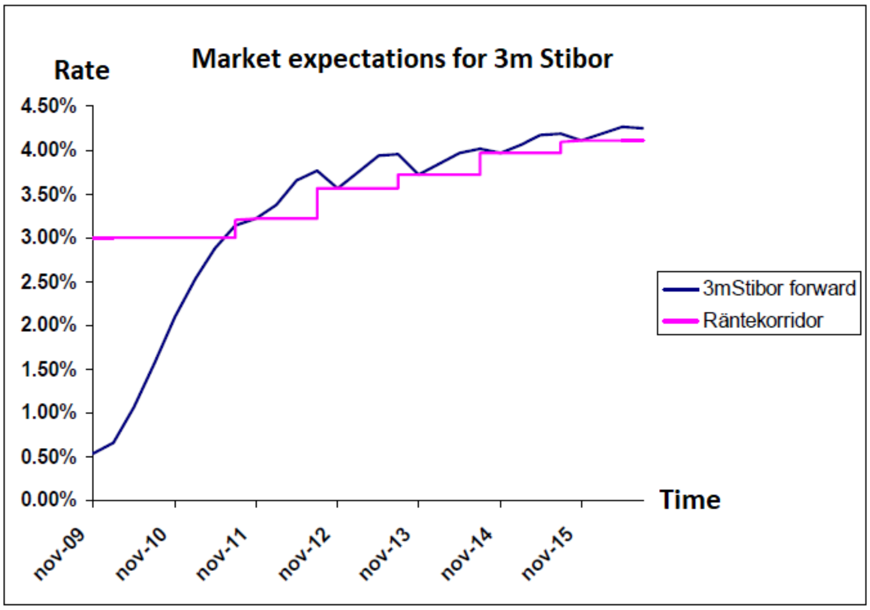

Figure 2.1: Diagram showing the potential payoff of *SEBO3058 Räntekorridor*, given that the 3m STIBOR rate follows the trajectory implied by the forward rates on the issue date (November 2009). The y axis shows potential coupon sizes and the 3m STIBOR rate. The x axis shows the dates at which the coupons are paid. The blue, curvy line shows the forward rate and the purple line with vertical kinks shows the predicted payoff. Source: SEB's marketing brochure (PDF link).

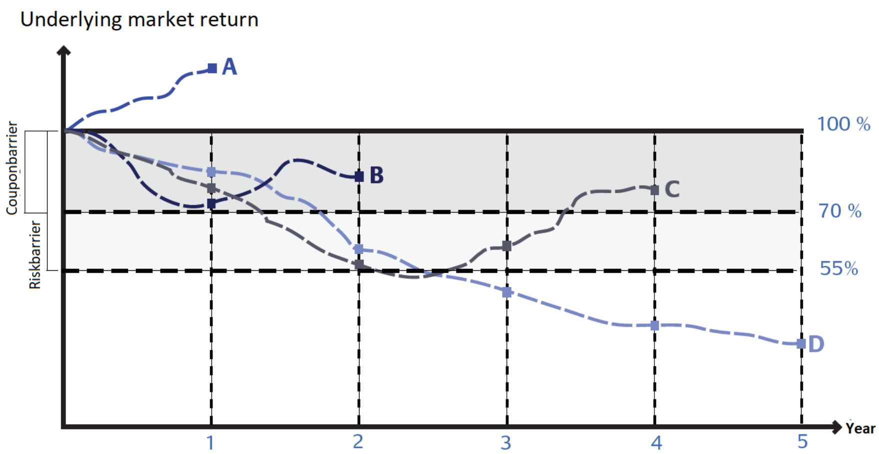

Figure 2.2: Diagram showing some potential payoff trajectories of *Double Autocall BRIC 5 (+/-)* depending on the development of the underlying. The x axis shows the yearly measuring dates and the y axis shows the value of the underlying asset basket. If the underlying value is above the topmost solid line the product pays a coupon and matures early (A). If the underlying value is between the solid line and the middle dotted line the product pays a coupon and matures early if it has paid two coupons (B and C). If the underlying value is between the dotted lines the product stays active and does not pay a coupon (C and D). If, at maturity the underlying value is below the bottommost dotted line, the product loses its capital protection and pays back a reduced amount equal to the fall in the underlying (D). Source: Mangold's marketing brochure (PDF link).

3 Data

3.1 Data collection

Information about expired structured products is not readily available. Therefore we hand collect our sample of structured products from the websites of the twelve largest Swedish structured product distributors. Our initial sample contains 1,160 products that all matured in 2016 and were sold by these distributors. We limit the study to products redeemed in 2016 as it makes the sample recent and relevant while also making the data collection possible within a reasonable time frame. We read each product's information web page (if available), marketing brochure and final term sheet to record information such as ISIN code, issuing date, intermediate coupon payments or redemption date. These information sources are not standardized in any way between distributors and issuers so we transform all the data we collect into a homogeneous format. If any of the relevant information is missing for a product, we drop it from the sample. This means we drop 66 products from one distributor that lack the required data for their entire range of products, and 83 products across the other 11 distributors, bringing the sample to 1,011 structured products.

For each of the 1,011 products now remaining in the sample we download daily bid price series, between the issue date and redemption date, from Bloomberg. Structured product data is not collected by Bloomberg but is instead reported voluntarily by the issuer. These bids are not observable to the investor but instead meant as an indicative valuation by the issuer to the distributor. The distributor then posts a bid towards retail investors that is reduced by an undisclosed margin on their website and on their respective market if the product is listed. In some dates, for unknown reasons, the issuer does not post any indicative bid. This means that price data can be very sparse or even non existent. Price data is wholly unavailable for 464 of products in our sample and they are subsequently removed. From the remaining sample, to ensure representative price series we also exclude 48 products that have bid prices on less than 85% of the days they were active. We choose 85% as a cutoff point as it is the highest cutoff point we can use where the removal of products from the dataset is minimal. We calculate monthly returns using these bid price series by comparing the price differences between the issuing date and a rolling window of approximately 30 days forward until the redemption date. Since there are gaps in the data, the rolling window varies somewhat. The average number of days in the windows vary between 28.5 and 31.2 for each product.

We use the bid prices instead of trading or ask price due to data availability, while inspecting a smaller subsample to confirm that the bid price leads the trade price and not vice versa. The distributor of a structured product always stands ready to purchase back any issued products by posting bids a public market where the products are listed or OTC, but trades are very rare. In the case that the distributor and issuer are different entities, the distributor in turn unwinds the product to the issuer who posts a higher bid in a similar way. This procedure creates the liquidity premium for product and lets the distributor hedge for price movements in the underlying assets while giving the investor the possibility of closing their position ahead of maturity.

After all exclusions, the final sample contains 499 structured products and the issuing dates for these structured products range from 2010 to 2016.

We use the payoff descriptions in the final term sheets and marketing brochures to assign each of these products with a primary feature and up to seven optional features using the dimensions in Table 2.1. The number of features gives each product a possible complexity score of 1 to 8, but the complexity score range for our sample of 1,011 products is initially 1 through 5. After bringing the sample down to 499 products, the range is instead 1 through 4 and the average score is 2.35.

3.2 Descriptive statistics

In Table 3.1, we show the representation of the primary features in our sample, per level of complexity. In Table 3.2 we show some descriptive statistics for our data. In the top part is the number of unique product combinations per level of complexity. Products of complexity 1 only have a primary feature, and there are only 3 primary features represented in this group. We list them and their descriptions here:

Call

The product offers a capital return of 100% plus a fixed participation in the rise of the underlying.

Altiplano

The product offers a capital return of 100% plus a series of fixed coupons in each subperiod if the underlying is above a predefined threshold.

Floater

The product offers a capital return of 100% plus a series of coupons that rise when the underlying reference rate rises.

Call is the most common with a relative frequency of 72% of complexity 1 products. Table 3.1 provides a more detailed look at the primary features represented in each level of complexity.

While complexity 2 contains 15 unique combinations, 74% of products of this complexity have the same two features; the *Call* primary feature and *Averaging* optional feature. The second most common combination represents 8% of complexity 2 products and the rest only 3% or less.

Complexity level 3 contains most unique combinations with 18, and the largest constituent has a relative frequency of 34%. The features in this product type are:

Primary feature: Call

The product offers a capital return of 100% plus a fixed participation in the rise of the underlying.

Path dependence: Averaging

The final underlying level is calculated as the average of the last readings over a given period (more than one month).

Underlying selection: 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.

The second and third largest products of complexity 3 have relative frequencies of 14% and 12%, respectively. The remaining 15 feature combinations all represent less than 3%, making complexity 3 the most diverse group of products.

There are 7 feature combinations in complexity level 4. 70% of complexity 4 products are Autocalls, which have the following features:

Primary feature: Altiplano

The product offers a capital return of 100% plus a series of fixed coupons in each subperiod if the underlying is above a predefined threshold.

Early redemption: Knockout

The product matures early if specific conditions are satisfied.

Underlying selection: Worst of option

The return is based on the participation in the performance of the worst performing underlying assets.

Exposure modulation: Reverse convertible

The product is capital guaranteed unless a performance criterion is not satisfied, in which case the capital return is reduced by the percentage fall in the underlying or the product pays back a predefined number of shares/bonds.

The second most common combination represents 16% of complexity level 4 products, and the remaining five combinations less than 3%.

In the middle part of Table 3.2, we show categories of underlying assets and how they are represented in the sample. Out of the 139 products with Nordic related assets, 129 have

Swedish stocks or stock indices as underlying. The *Developed* category contains underlying assets such as North American, Japanese and non-Nordic European stocks or indices. *Emerging* contains Brazil, Russia, India, China, Africa and most of Asia.

Finally, the bottom part of Table 3.2 shows the distribution of initial time to maturity of products in our sample. Some products can be redeemed early under certain conditions and in those cases the listed maturity will not match the actual life span of the product. All but 5 products in our sample have maturities ranging from between 1 to 5 years, with 3-5 years being about twice as common with 307 versus 185 products for the span 1-3 years.

	Primary feature						
Complexity score	Altiplano	Bull bear	Call	Digital	Floater	Pure income	Total
1	3	-	21	-	1	-	25
2	11	4	277	1	14	-	307
3	-	-	88	5	3	2	98
4	50	-	18	-	1	-	69
Total	64	4	404	6	19	2	499

Table 3.1: Primary feature frequency per level of complexity.

	Complexity score							Total
	1	2	3	4				
No. of unique feature combinations	3	15	18	7				43
			Underlying asset					
	Nordic	Developed	Emerging	Commodities	Global	Currencies	Other/misc	
No. of products	139	137	104	45	41	26	7	499
		Time to maturity						
	Short (< 1 year)	Medium ($1 - 3$ years)	Long ($> 3 - 5$ years)	Very long (> 5 years)				
No. of products	3	185	307	2				497*

Table 3.2: Descriptive statistics for the 499 products in our dataset. The top part shows the number of unique combinations of primary and optional features, per level of complexity. The middle part shows frequency of products with a certain category of underlying asset. The bottom part shows the planned time to maturity at issuance. *Two products do not have time to maturity data

4 Results

4.1 Complexity and returns

To measure how complexity affect returns in structured products we setup a panel regression model of the following form:

$$R_{it} - R_{ft} = \beta_0 + \sum_j \gamma_j cplx_{ji} + \sum_j \delta_j x_{ji} + \sum_j \theta_j z_{jit} + \varepsilon_{it} \tag{4.1}$$

The dependent variable is a time series of product i's excess return over the risk free rate; R_{it} is the monthly return for product i in month t and R_{ft} is the risk free rate in month t which we proxy for using Swedish treasury bills of 3 month maturity. The explanatory variables are complexity and varying control variables. In the equation complexity ($cplx_i$) is a set of ordinal dummy variables with four levels and complexity level one as the base case. The control variables are separated into time-invariant (x_i) and time-variant (z_{it}). The time-invariant variables are: *Distributor*, *Primary feature*, and *Complexity#Primary* which is the interaction term between *Complexity* and *Primary feature*. The time-variant variables are: *Time to maturity* and *Realized volatility*.

The results of this regression model are presented in Table 4.1.

Before adding any control variables (specification 1), it appears as if moving from a complexity of 1 to 2 increases average monthly returns by 0.209% and from complexity 1 to 4 by 0.286%.

However, different distributors create their own unique products so we control for distributor

Complexity score	Monthly returns (1)	(2)	(3)	(4)	(5)
2	0.209**	0.139	-0.176	-0.181	-0.181
	(0.088)	(0.095)	(0.320)	(0.312)	(0.312)
3	0.043	0.063	-0.510*	-0.511*	-0.511*
	(0.096)	(0.103)	(0.291)	(0.297)	(0.297)
4	0.286**	0.141	0.002	0.075	0.075
	(0.141)	(0.112)	(0.222)	(0.244)	(0.244)
Constant	0.076	-0.311*	-0.163*	-0.055	-0.055
	(0.083)	(0.187)	(0.085)	(0.096)	(0.096)
Controls					
Distributor	-	Yes	Yes	Yes	Yes
Primary feature	-	Yes	Yes	Yes	Yes
Complexity#Primary	-	-	Yes	Yes	Yes
Time to maturity	-	-	-	Yes	Yes
Realized volatility	-	-	-	-	Yes
Observations	21,506	21,506	21,506	21,423	21,423
Number of isin	499	499	499	497	497
R^2 (within)	0.000	0.000	0.000	0.001	0.001
R^2 (between)	0.045	0.215	0.256	0.237	0.238

Table 4.1: Results of five panel regressions with monthly returns as the dependent variable, complexity as the explanatory variable and different control specifications. Standard errors clustered at individual product level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

in our next specification. Further, within each complexity group are products with differing characteristics. As such we also control for the primary feature of each product.

With these two control variables the difference between complexity levels is no longer statistically significant. The constant now changes sign and is statistically significant (p-value less than 0.1) which suggests that the products, on average, produce negative excess return of approximately -0.3%.

Since the primary feature of a product affects the payoff in a major way, we add the interaction term between primary feature and complexity score to capture differences in the complexity-returns relationship for different types of products. Incorporating this control in specification (3) changes the results. Complexity score 2 has a slightly negative difference (though it is statistically insignificant) while complexity score 4 does not seem to differ at all from complexity score 1. Now instead, complexity score 3 has a negative difference of more than -0.5%. The change in results indicates that there is indeed a difference in the complexity-return relationship for different primary features.

In specification (4) and (5), *time to maturity* has a positive and statistically significant (p-value<0.1) coefficient but has a minor effect on the coefficient on *complexity score*. This signifies that as the product gets closer to maturity, the true value of the product becomes more certain and mispricing is reduced, leading to higher returns. The constant in these specifications remains negative but is now insignificant.

Realized volatility is a good determinant of returns in some cases so we add it in specification (5). For our sample, it has essentially no effect on the rest of the model and a p-value greater than 0.1 so (5) can be mostly disregarded. Because of the lack of interpretive power we refer to Occam's razor and focus on model specification (4) in the result tables below.

These results show a negative correlation between complexity and returns, at least for a certain difference in complexity.

The majority of products of complexity 1 are protected calls and complexity 2 protected calls with an *Averaging* feature. Arguably, the *Averaging* feature does not change the product much in terms of complexity which is an explanation for the small difference between complexity 1 and 2. *Averaging* means that the final underlying growth is calculated as an average of the last (often 13) monthly observations instead of simply using the final observation. Implying it actually reduces volatility for the product as it gets closer to maturity. So the final observation at maturity only has a small impact (1/13) on the final return compared to when there is no averaging feature and all of the return is dependent on the final observation. Therefore it reduces the delta of the product as it gets closer to the final observation.

The group of products of complexity 3, while still having *Call* as their most common primary feature, have a much larger variation in optional features. This means that going from 1 to 2 dimensions is significantly less impactful than going from 1 to 3.

Complexity 4 products are very different from the rest, as the majority of products in that category have a different primary feature; *Altiplano*. The similar returns between complexity 1 and 4 therefore is a conundrum, but could be a spurious result due to the specific market conditions present during the sample period. We therefore adjust the returns for market conditions using a factor model that includes linear and nonlinear market returns as factors in our second regression.

4.2 Complexity and risk-adjusted returns

In our second regression model we use a two step approach to account for the market return and the nonlinearity of the payoffs. Following Glosten and Jagannathan (1994), Agarwal and Naik (2004), Bauer et al. (2009) and Entrop et al. (2016), we perform an individual regression (Equation 4.2) for every product. These regressions provide individual alphas for the products which we then use as the dependent variable in a regression (Equation 4.3) that is otherwise identical to the one in the previous section (Equation 4.1).

The results of our second regression model (Equation 4.3) are presented in Table 4.2.

The risk-adjusted returns are obtained using the following factor model:

$$R_{it} - R_{ft} = \alpha_i + \beta_{OMX} R_{OMX_t} + \beta_{ATMC} ATMC_t + \beta_{ATMP} ATMP_t + \epsilon_t \tag{4.2}$$

where R_{it} is the monthly return for product i in month t, R_{ft} is the risk free rate in month t, R_{OMX_t} is the monthly excess return for the OMX30 index in month t and $ATMC_t$, and $ATMP_t$ are the excess returns for an at-the-money call (put) strategy, respectively, in month t.

Since structured products most often have nonlinear payoffs, simply adjusting returns by the market factor would be insufficient as it only represents the linear returns of the market. We add the call and put factors to incorporate the nonlinearity. Performing this regression adjusts the returns for movements that are simply due to market fluctuations which would incorrectly reward market risk. The alphas are now mean returns that the product generates above and beyond the standard strategies.

We collect these alphas (one for each product) and perform a cross sectional regression with identical controls as in Equation 4.1, with α_i as the dependent variable:

$$\alpha_i = \beta_0 + \sum_j \gamma_j cplx_{ji} + \sum_j \delta_j x_{ji} + \sum_j \theta_j z_{jit} + \varepsilon_{it} \tag{4.3}$$

In equation 4.2 we choose to use the OMX30 index as market factor as it (or stocks included in this index) represent the single biggest category of products in our sample with a roughly 30% share. Expanding the model with a broader index or more factors is certainly possible for more accurate value estimates. However, the choice of index matters less for the relative performance rank which is the most important in our analysis (Glosten and Jagannathan, 1994).

The ATMC and ATMP factors are constructed as follows, respectively: on the first date, an at the money call (put) option with 3 month maturity and the OMX30 index as its underlying asset is purchased. The following month, that option is sold and another is purchased with 3 month maturity from that date and so on. This produces monthly returns for the call (put) option strategy that represent the nonlinear risk inherent in the majority of structured products. These factors are easily implementable strategies that the investor can choose in combination with or instead of the structured products.

Historical call and put option prices are calculated from historical implied volatility gathered from Bloomberg and using the Black-Scholes Merton model for option pricing. Since the implied volatility is calculated using real prices, this reverse engineering gives us a close estimate of the real prices on each date.

We see that risk-adjusting the returns changes both the coefficients and their significance in all model specifications. Products of complexity 2 yield slightly positive (approximately 0.1%) and significant returns no matter which controls are used. As in the previous regression, we consider the controls used in specification 3 and 4 most valid. Even after risk-adjusting the returns, products of complexity 3 have a negative coefficient of between -0.02% and -0.19% which is a similar magnitude as in the first regression. The worse performance of products of complexity 3 is partially explained by the factors in the risk-adjusting model, which indicates

	Risk-adjusted returns (α_i)				
Complexity score	(1)	(2)	(3)	(4)	(5)
2	0.070***	0.037***	0.092*	0.104**	0.104**
	(0.011)	(0.013)	(0.047)	(0.047)	(0.047)
3	-0.022	-0.074***	-0.185***	-0.116**	-0.116**
	(0.015)	(0.015)	(0.054)	(0.052)	(0.052)
4	-0.092***	-0.118***	-0.577***	-0.526***	-0.526***
	(0.032)	(0.019)	(0.057)	(0.060)	(0.060)
Constant	-0.007	-0.323***	-0.050***	-0.085***	-0.085***
	(0.011)	(0.037)	(0.013)	(0.015)	(0.015)
Controls					
Distributor	-	Yes	Yes	Yes	Yes
Primary feature	-	Yes	Yes	Yes	Yes
Complexity#Primary	-	-	Yes	Yes	Yes
Time to maturity	-	-	-	Yes	Yes
Realized volatility	-	-	-	-	Yes
Observations	21,506	21,506	21,506	21,423	21,423
R^2	0.008	0.065	0.091	0.086	0.086

Table 4.2: Results of five cross sectional regressions with risk-adjusted return alphas as the dependent variable, complexity as the explanatory variable and different control specifications. Heteroscedasticity robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

that in the first regression most of the difference is due to market risk.

For complexity 4 products, the coefficient is approximately -0.1% in the first two specifications but jumps to roughly -0.55% in specifications 3 to 5. This change in result is revealing, as it shows that complexity 4 products were before incorrectly showing higher returns that were in fact due to the movement of the market as a whole. The group of products with complexity score 4 is dominated by *Autocalls* which is a type of product that is capital protected, but only to a certain point, and it is one of the few types of products that is not guaranteed to stay active until maturity. Due to these characteristics, an Autocall is naturally more risky and more difficult to be assigned a fair value compared to less complex products. Our results show that investors are inadequately rewarded for accepting this risk. The poor performance could be due to the increased difficulty in assigning a fair value to these products because there are many more possible scenarios that determine the payoff.

As we mention in Section 4.1, complexity 3 is very diverse in terms of what optional features are added onto the *Call* primary feature. The negative coefficient on complexity 3 in this regression shows that the jump in complexity from 2 to 3 is still there, and that it affects investor returns adversely. The positive coefficient on complexity 2 shows that adding a little bit of complexity is good for the investor. It is plausible that the *Averaging* feature, which is by a wide margin the most common optional feature in complexity 2, has a positive effect on returns in our sample.

In the first regression, the coefficient on complexity 3 is significant while the coefficient on 2 and 4 are not. In the second regression, the coefficient on complexity 2 is positive while the coefficients on 3 and 4 are increasingly negative. We therefore suspect that the relationship between higher complexity and lower returns is nonlinear.

4.3 Nonlinear extension

4.3.1 Continuous complexity and monthly returns

To capture the nonlinearity and as a robustness check, we demean complexity and treat it as a continuous variable. Demeaning the complexity variable means the possible values range from -1.35 to 1.65 with mean 0 and a standard deviation of 0.74. We run three panel regressions where subsequently, complexity squared and complexity cubed are added. This regression takes the following form:

$$R_{it} - R_{ft} = \beta_0 + \beta_1 cplx\_dem_i + \beta_2 cplx\_dem_i^2 + \beta_3 cplx\_dem_i^3 + \sum_j \delta x_{ji} + \sum_j \theta z_{jit} + \varepsilon_{it} \quad (4.4)$$

where $cplx\_dem_i^2$ and $cplx\_dem_i^3$ are added depending on the specification. The controls used are the same as in specification (4) in Section 4.1 as these controls are arguably the most valid. The results can be seen in Table 4.3.

In specifications (1) and (2) a linear relationship is significant while (3) points to a nonlinear relationship. Both (2) and (3) have significant F-tests of joint significance, which shows conflicting results. However, we believe that the relationship is high degree nonlinear since a second degree relationship would imply that products below the mean, i.e. complexity 1 and 2, yield similar results to those above it, i.e. complexity 3 and 4. Since this does not appear to be the case in our previous results, specification (3) is more in line with those findings. A joint F-test including only the linear and cubed values is significant with a p-value of less than 0.01.

The case for nonlinearity is not entirely conclusive when taking all specifications into account, but they do all suggest that low complexity products are relatively better than high complexity products. Adding all the effects together in the third specification shows that investors lose compared to the risk-free rate no matter the complexity but complexity 3 loses the most while complexity 1 loses the least.

	Monthly returns		
Complexity score	(1)	(2)	(3)
cplx_dem	-0.103***	-0.147***	-0.343
	(0.029)	(0.053)	(0.332)
$cplx\_dem^2$		-0.150	0.060**
		(0.143)	(0.031)
$cplx\_dem^3$			0.096
			(0.143)
Constant	-0.195	-0.529	-0.390**
	(0.127)	0.349	(0.207)
Joint significance (χ^2)		12.94***	21.92***
Observations	21,423	21,423	21,423
R^2 (within)	0.001	0.001	0.001
R^2 (between)	0.244	0.244	0.244

Table 4.3: Results from three panel regressions with excess monthly returns as the dependent variable and demeaned complexity, treated as a continuous variable, and a set of controls as the explanatory variables. Standard errors clustered at individual product level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.3.2 Continuous complexity and risk-adjusted returns

The second regression, using risk-adjusted alphas as dependent variable and continuous complexity takes the following form:

$$\alpha_i = \beta_0 + \beta_1 cplx\_dem_i + \beta_2 cplx\_dem_i^2 + \beta_3 cplx\_dem_i^3 + \sum_j \delta_j x_{ji} + \sum_j \theta z_{jit} + \varepsilon_{it} \tag{4.5}$$

Regression 4.5 is identical to Regression 4.4 except that the monthly excess returns are replaced with the risk-adjusted alphas from Equation 4.2.

The results from this regression are presented in 4.4. In all three specifications the linear relationship is negative and significant between increasing complexity and returns. As is the case in the previous section, the squared complexity variable is not significant in the second specification. The results in Section 4.1 show that complexity 2 products have higher risk-adjusted returns on average compared to the other complexities which a model with cubed values would be better at capturing. We see that this is the case in specification (3). Adding the cubed values improves the significance of the squared, and the cubed variable is jointly significant in combination with each and both of the linear and squared variables.

Summing the effects in specification (3), we see that for higher complexities, which have positive values in this continuous form, the effects of the squared and cubed variable cancel each other out. This means that moving from complexity 3 to 4 gives a mostly linear reduction in returns. For lower complexity products, i.e. 1 and 2, the nonlinear effect is more pronounced. Again, this can be explained by the improvement in returns when going from complexity 1 to 2. As we recall from Section 4.2, complexity 2 is dominated by products with a *Call* primary feature and *Averaging* optional feature that smooths out the last months' returns. When considering the relationship between complexity and risk-adjusted returns, then, there appears to exist a weak nonlinearity that is mostly there for lower complexity products.

The results from this regression confirm those in Section 4.2. Medium complexity products perform similarly, or slightly better than the lowest complexity while increasing complexity to the highest levels reduces risk-adjusted returns. However, structured products of all complexity levels have negative risk-adjusted returns compared with the simple strategy of our factor model.

	Risk-adjusted returns		
Complexity score	(1)	(2)	(3)
cplx_dem	-0.057***	-0.057***	-0.112**
	(0.005)	(0.009)	(0.058)
cplx_dem^2		-0.002	-0.027***
		(0.025)	(0.005)
cplx_dem^3			0.027
			(0.025)
Constant	-0.163***	-0.158**	-0.119***
	(0.021)	(0.062)	(0.036)
Joint significance (χ^2)		55.57***	346.78***
Observations	21,423	21,423	21,423
R^2	0.090	0.090	0.090

Table 4.4: Results from three regressions with risk-adjusted return alphas as the dependent variable and demeaned complexity, treated as a continuous variable, and a set of controls as the explanatory variables. Heteroscedasticity robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5 Conclusion

Our research investigates if higher complexity leads to lower returns for investors in structured products through a series of regressions. We hand collect a unique sample of 499 structured products sold in Sweden that matured in 2016 and assign each of them with a complexity score from 1 to 4 out of a possible 8.

The regressions in Sections 4.1 and 4.2, while not producing the exact same results, tell similar stories. It appears as if adding too much complexity has detrimental effects on returns and risk-adjusted returns. Complexity 2 products perform better than complexity 1 in our second regression with risk-adjusted returns and the difference between the two complexities is insignificant in the first regression. Once you go over a certain hump of complexity, however, the products become too difficult to value and the investor loses or is taken advantage of by the distributor through higher hidden fees (Célérier and Vallée, 2017). It could also be the case that certain optional features that are not present in any major way in complexity 2 products have a large negative effect compared to the simple *Averaging* feature that smooths out large swings in underlying asset price towards the end of a product's life.

The robustness check in Section 4.3.1 confirms the negative relationship between higher complexity and returns. However, these results cannot confirm conclusively if the relationship between complexity and returns should be modeled linearly or nonlinearly. We think an argument can still be made that there is nonlinearity because only complexity score 3 has a negative and significant coefficient in Table 4.1 and complexity-square is significant in the nonlinearity check in Table 4.3.

The risk-adjusted robustness check in Table 4.4 again confirms our results of lower returns when complexity increases, as in Section 4.2. Here, there is also evidence of weak nonlinearity where complexity 2 performs slightly better than the rest and complexity 3 and 4 are increasingly worse for investor returns.

In conjunction, these results mean we can tentatively confirm our hypothesis that an increased complexity decreases returns in structured products. Depending on what optional feature is added to a structured product, arguably the returns can increase for small additions in complexity. For larger jumps in complexity, the products become difficult for the investor to value, no matter what features are added, and that is where we see a reduction in returns. This is also a theoretical argument for the nonlinearity of the complexity-returns relationship which we show exists, though not conclusively. No matter how you slice it, in our sample structured products of all complexities perform equal to or worse than the reference assets.

Our results fall in line with the literature. For example, Célérier and Vallée (2017) find that in low interest environments structured products issuance tends towards more complex products with higher chance of complete losses, since zero coupon bonds become more expensive and are often one of the instruments included in capital protected structured products. In Sweden, the interest rate has been steadily declining during the years of issuance in our sample and has even reached negative territory which implies that the products in Sweden tend to become more complex. While we only analyze products in 2016, Célérier and Vallée (2017) show that the trend in Europe between 2002 and 2010 has been a reduction in complexity 1 in favor of complexity 3, 4 and much higher (5 and larger). In our sample of 499 products, only 6% are of complexity 1 compared with 20% of complexity 3 and 10% of complexity 4.

Earlier research has also shown that more complex products make it easier for distributors and issuers to hide higher markups (Henderson and Pearson, 2011). In the case where these markups are contained in the price, the returns will be lower in our analysis. Wallmeier and Diethelm (2009) analyze *Multi-Asset Barrier Reverse Convertibles* (MBRC) in Switzerland that are very similar to the Autocalls sold in Sweden, the worst performing and most dominant product of complexity 4 in our sample. They find that MBRCs are overpriced by 3.4% or more compared to a theoretically modeled value. A caveat when looking at so few years of issuance, the market for structured products will follow certain trends in terms of underlying assets and payoff profiles that introduces a bias in the sample. Adjusting for the market risk as we do in our second regression model helps in alleviating this problem.

Our results show what many regulators around the world have already found, that the market for structured products is unfair to investors who may need regulatory protection against the more complex products that distributors invent. Barring regulatory pressure, investors at least need to be educated in the workings of the structured financial market to better understand the riskiness of these products. Simply through our data collection we find that the marketing material and naming conventions of the structured products market are rarely in favor of the investor. They highlight best-case scenario returns and are highly limited in what they reveal about the components that enter into the product. The final terms between issuer and distributor, meanwhile, can be difficult to understand even for experts in this market. We believe a harmonization among distributors in naming conventions and more transparent product descriptions would benefit investors and the market as a whole.

For future work, we recommend expanding the sample to include more years of expiry and issuance. Simply performing our research again in a couple of years would yield interesting results seeing as the trends in the structured product market are likely to shift. Further, since hedging and diversification are possible reasons for investors to purchase structured products, analyzing entire investor portfolios that include structured products could provide a rational explanation for the demand for structured products which we feel is missing beside the explanations using behavioral biases.

We consider three possible extensions of our work highly relevant. First, adding additional measures of complexity to the analysis provides more robustness to the results and can show dynamics that we are unable to. As two examples, Célérier and Vallée (2017) also look at payoff description length and the number of possible payoff scenarios. Second, our complexity score only counts the number of features in a product's payoff. It does not take into account that different optional features may be more or less difficult to understand than others for the investor. Third, the two primary features *Call* and *Altiplano* are heavily overrepresented compared to other primary features for the products in our sample. Performing a separate analysis that only includes these might reveal new facts about the complexity-returns relationship.

We leave these possible extensions for other researchers that are interested in this highly unique and innovative financial market.

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