Extrapolation and Complexity*

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Abstract

The market for structured retail products (SRPs) has grown rapidly in sales volume and complexity in last two decades across the world. Motivated by this phenomenon, this study seeks to understand why unsophisticated retail investors purchase complex financial products and proposes investors' extrapolative expectations as an explanation for the demand for complex financial products using a comprehensive data set on SRPs. I find that products with higher past returns have enjoyed higher sales growth, even though past returns do not predict future performance. Interestingly, this extrapolative effect is stronger for more complex products. Extrapolation, combined with investors' salient thinking (Célérier and Vallée, 2017), leads to the observation of greater popularity of more complex products that happen to deliver better past performance and offer higher headline rates. While there is some evidence of financial intermediaries exploiting investors in early part of the sample, my results further suggest that the rapid market growth has led to more competition among intermediaries, which in turn disciplines exploitation.

Keywords: Extrapolative Expectation, Exotic Options, Financial Derivatives, Financial Engineering, Salient Thinking, Structured Retail Products

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1 Introduction

Understanding the market for complex financial products has been a long-standing challenge in financial economics. This paper studies the rapid growth in sales volume and complexity observed in the market for structured retail products (SRPs), which is a good laboratory to study the market for complex financial products. The existing literature on complex financial products focuses on the exploitation view that financial intermediaries deliberately mislead and missell complex financial products to investors (Carlin, 2009; Célérier and Vallée, 2017; Egan, 2019; Henderson and Pearson, 2011; Henderson et al., 2020). While there is strong evidence of exploitation in the market for SRPs, it is difficult for this view to fully explain the persistent growth of this market for over two decades. For example, the market for global equity-linked SRPs has experienced sustained growth from a global sales volume of only \$50 billion in 2001 to nearly \$250 billion in 2015. Exploitation may explain the initial motive for financial intermediaries to offer such products at the beginning, but it remains a puzzle why the investor demand continued to increase after so many years, as one would expect investors to eventually suffer investment losses and realize the exploitation. Therefore, a fundamental question, "Why do unsophisticated retail investors purchase complex financial products?," deserves to be further studied and explored.

In this paper, I examine an alternative mechanism to address this question. An extensive literature in behavioral finance has suggested that in predicting future asset returns, retail investors tend to extrapolate past returns (Amromin and Sharpe, 2009; Greenwood and Shleifer, 2014; Vissing-Jorgensen, 2003). This extrapolative behavior offers a potential explanation for investors' demand for SRPs along with other explanations such as salient thinking (Célérier and Vallée, 2017) and brokers' conflicts of interests (Egan, 2019) studied in the previous literature. Specifically, I hypothesize that investors with extrapolative expectations estimate expected future returns of SRPs based on their past returns, rather than their characteristics that determine their expected future returns. The presence of such extrapolative investors in turn motivates financial intermediaries to offer a large variety of SRPs so that some of them would offer high returns and attract more investor demand over time. To the extent that complex SRPs are more difficult for investors to comprehend, they may rely even more on extrapolating past returns. Consequently, investor demand for more complex SRPs would be more exposed to their past returns.

Financial institutions, such as investment banks, sell SRPs that package exotic options, linked to underlying assets such as stock market indexes, with bonds. The most notable feature of the

SRP market is rapid growth in sales volume. In fact, the global equity-linked SRP sales volume nearly quadrupled from about $50 billion in 2001 to approximately $250 billion in 2015. Another interesting feature of this market is increasing complexity. Autocallable products, also known as autocalls, are one of the the most complex types of SRPs. Notwithstanding their complexity, autocalls have experienced remarkable sales growth, higher than other SRP products, which resulted in a market share of nearly 50% in the global SRP market in 2015. Similar trends are also observed in the largest SRP market, the United States. Given the risks and complexities associated with SRPs and the market's fast growth, which have been highlighted by the U.S. Securities and Exchange Commission (SEC), understanding what affects SRP investors' purchase decisions should prove highly valuable (Starr, 2015).[1]

In this research I study the market for SRPs using a comprehensive data set comprising 71,300 individual SRPs issued in the United States between 2001 and 2016. All SRPs are different in terms of payoff structures, parameters, complexities, and so on. Such a rich cross-sectional variation across SRPs is crucial to identify mechanisms that determine demand for complex financial products. I show that SRP investors possessed extrapolative expectations and they exhibited stronger extrapolation when purchasing more complex products by examining the relationship between sales and past returns. Extrapolation, combined with investors' salient thinking (Célérier and Vallée, 2017), provides important clues for explaining the increasing complexity and the growing market size. In addition, I provide evidence that this market has become more competitive and transparent, and therefore exploiting investors has become more difficult.

In a formal test for extrapolation, I find that the past returns on SRPs have a statistically and economically significant effect on future sales of SRPs. Furthermore, sales of more complex SRPs are more sensitive to their past return, compared with those of less complex products. This result is consistent with investors' extrapolation and it is suggestive that investors are subject to more severe extrapolation when purchasing more complex products possibly because understanding products is harder for more complex products. This result is not explained by investors' rational expectations. Contrary to what investors with extrapolative expectations believe, I show that neither past returns nor sales volume predicts the performance of newly issued SRPs. This suggests that the positive relationship between SRPs' past returns and sales is not driven by rational information extraction from past returns on SRPs. Multiple survey findings collectively show that SRP investors gener-

[1]Amy M. Starr, Structured Products - Complexity and Disclosure - Do Retail Investors Really Understand What They Are Buying and What the Risks Are? - `https://www.sec.gov/news/speech/speech-amy-starr-structured-products-.html`

ally have only limited background knowledge about SRPs, which further corroborates investors' behavioral bias.

One may think that financial advisers who want to deliberately exploit investors' extrapolation bias could only recommend SRPs that performed well in the past, which could drive the results. Importantly, however, in the untabulated subsample analysis excluding SRPs sold by twenty brokerage firms with highest incidence of misconducts reported in Egan et al. (2019), I find that the effect of extrapolation does not become weaker, which mitigates the concerns that extrapolation is entirely driven by financial intermediaries' misconducts.

While extrapolation is an important mechanism that explains the demand for SRPs, it is plausible to expect that SRP investors' decision making processes should be more complicated given the complex nature of SRPs. I conjecture that investors rely on multiple approaches to deal with financial complexities of SRPs and test two main hypotheses, extrapolation and investors' salient thinking, jointly. I find that these two mechanisms provide important clues regarding the increasing complexity.

Salient thinking hypothesis studied in Célérier and Vallée (2017) posits that SRP investors tend to be attracted by a salient feature, headline rate, which is the maximum return that an SRP can generate when underlying asset performs well. I first find that more complex products tend to offer higher headline rates, which is consistent with the findings of Célérier and Vallée (2017). Moreover, I find that more complex products, especially autocalls, perform better than other products *ex-post* in my sample. A regression analysis based on the restricted SRP sample that offer headline rates shows that both past return and headline rate explain sales of SRPs and the effects are statistically and economically significant. Importantly, extrapolation and salient thinking do appear to be separate drivers that explain the demand for SRPs. Correlation between past return and headline rate is small and negative (-0.161). Overall, my results suggest that both extrapolation and salient thinking are crucial in SRP investors' decision making processes. Furthermore, stronger extrapolation for more complex products and salient thinking, combined with better ex-post performance and higher headline rates of more complex products, provide a clear explanation of the increasing complexity. The rapidly increasing market share of more complex products eventually contributes to the rapid growth of the overall SRP market.

A natural follow up question at this juncture is how financial intermediaries react in the presence of investors' extrapolation bias. On the one hand, it is possible that exploitation by financial intermediaries persists and the market remains "dark," as consistently highlighted in the previous literature. In that case, markups charged by financial intermediaries should remain high over a long period and investors should keep buying the products. On the other hand, it is also plausible that the market has become more competitive, and therefore the effect of exploitation could have become weaker.

To answer this question, I first show that product markups have fallen over time based on S&P 500-linked SRPs sample. Early studies (Henderson and Pearson, 2011; Stoimenov and Wilkens, 2005) provide evidence that markups for some SRPs are too high to be justified. In my sample, the median annualized markup was about 1.9% in 2004, which means that products with a one-year (three-year) term of maturity charged a markup of 1.9% (5.7%) in 2004. Such a high markup is consistent with findings from the early studies. However, the median annualized markup decreased to nearly 0.5% in 2016. During this time period, the number of issuers has consistently increased. This result is consistent with recent studies highlighting low markups of SRPs issued by members of Deutscher Derivate Verband in 2013 and 2016 (Deutscher Derivate Verband, 2015; Muller et al., 2017). Overall, issuers have lowered markups and the effect of exploitation has become weaker, which is consistent with the pattern that the market has become more competitive.

I provide evidence that the market has become more transparent as well. Since 2013, issuers in the United States have been required to provide the fair value of any SRP on the first page of its prospectus. The fair value is an essential element in calculating the annualized markup, and therefore one of the most important information in decision-making. I compare the annualized markups calculated based on reported fair values with annualized markups estimated based on a stochastic volatility model (Heston, 1993) and find that issuers have reported quite accurate fair values, which resulted in improved transparency of the SRP market.

If exploitation motives by financial intermediaries are strong, banks could charge high markups or brokers could charge high sales commissions when they expect that demand for particular SRPs will be high due to solid past performance. I find higher past returns predict slightly lower future markups and sales commissions. Taken together, my results suggest that the effect of exploitation is becoming weaker. Market based mechanisms, such as increased competition, could have prevented issuers and brokers from easily exploiting unsophisticated investors.

My research contributes to several strands of the literature. First, this study enriches the literature on complex financial products. (Carlin, 2009; Carlin and Manso, 2010; Coval et al., 2009). The vast majority of existing papers focus on highlighting exploitation by financial intermediaries (Stoimenov and Wilkens, 2005; Gabaix and Laibson, 2006; Henderson and Pearson, 2011; Bordalo et al., 2015; Egan et al., 2019; Célérier and Vallée, 2017; Ghent et al., 2017; Egan, 2019) while recent studies find mixed results (Auh and Cho, 2019; Döhrer et al., 2013; Deutscher Derivate Verband, 2015; Calvet et al., 2017; Muller et al., 2017). My results are generally consistent with the existing literature in the sense that the markups were high in early part of my sample. I add to this literature by showing the salient patterns of decreasing markups and increasing competition over time. More importantly, the accurate information on markups, which was hidden in early periods, has been publicly available since 2013, and therefore exploitation through charging high markups has become more difficult.

Second, my research adds to the developing literature on SRPs, which started from a seminal work, Henderson and Pearson (2011). Several recent papers make a contribution in addressing the question of why unsophisticated investors buy complex SRPs (Célérier and Vallée, 2017; Egan, 2019). Some use alternative samples to document the mispricing of SRPs (Bauer et al., 2016; Vokata, 2018). Another strand of research studies some other issues not directly related to the investment motive of SRPs (Henderson et al., 2015; Henderson et al., 2020). My paper is part of this developing literature. I provide evidence that the investor demand for SRPs is at least partly explained by investors' use of extrapolation to estimate the returns of complex financial instruments by analyzing the largest sample in this literature.

Third, my study introduces an important mechanism that drives financial innovation. Allen and Gale (1994) and Duffie and Rahi (1995) highlight the benefit of risk sharing in financial innovation through market completion. Simsek (2013), however, provides an alternative view. Simsek (2013) proposes that financial innovation can encourage more speculation due to the belief disagreements between investors, and therefore makes investors' portfolios riskier. Gennaioli et al. (2012) and Arnold et al. (2018) emphasize the role neglected risk by investors plays in understanding financial innovation. My paper shows that another mechanism, extrapolation, might be essential to explaining financial innovation. More specifically, extrapolation explains what types of products are adopted and abandoned in financial innovation. My results show that products with high ex-post performance are adopted fast and products which provided very poor ex-post performance experience a sharp decline and are eventually abandoned.

Finally, my study provides empirical evidence on how investors deal with financial complexity. Brunnermeier and Oehmke (2009) suggest several approaches that bounded rational investors can take to deal with financial complexity. For example, investors can divide the complex products into several pieces that are relatively easy to analyze. Also, they can employ a simple pricing model, such as the Black-Scholes Model (Black and Scholes, 1973). I add to this literature by showing that if investors cannot use these systematic approaches because products are very complex, investors tend to rely heavily on a simple approach, *extrapolation*.

2 Institutional Background

2.1 What are structured retail products?

Structured retail products are retail financial products whose performance is determined by complex payoff structures that vary with the performance of underlying assets. The payoff structures of SRPs are generally nonlinear functions of the performance of the underlying assets. Additionally, these payoff structures of SRPs are generally more complex than those of plain vanilla options and they take various forms across multiple types of products. SRPs are based primarily on equity indexes or individual stocks but there are also SRPs that provide exposure to other underlying assets such as commodities, exchange rates, or alternative indexes.

According to Structured Retail Products, Ltd.,[2] the SRP market has experienced steady growth and, as of 2016, assets under management on this market total is about \$1.92 trillion globally and about \$8 trillon worth of products have been issued since the market first opened. The largest market in terms of assets under management is the United States. As of 2016, the assets under management in the United States totaled \$367 billion, followed by South Korea with \$143 billion worth of assets under management.

When purchasing SRPs, investors consult with brokers. Throughout a meeting with investors, brokers comprehend the risk appetites of the investors and recommend suitable SRPs. Brokers are compensated by sales commissions, which represent fixed proportions of total amount invested by investors. A sales commission is decided through negotiation between an issuer and a brokerage firm before a product is marketed and it varies across products.

Since 2001, when the major markets began to become popular, SRPs markets have experienced significant change. The most notable change is the the rapid growth in sales volume and complexity.

[Insert Figure 1 here.]

Figure 1, Panel A displays global sales of equity-linked SRPs. While global equity-linked SRPs sales volume was approximately \$50 billion in 2001, it increased to nearly \$300 billion in 2007,

[2] `https://StructuredRetailProducts.com`

followed by a sharp decrease in the midst of the financial crisis. SRP sales have recovered since then and the sales volume was approximately $200 billion in 2016. Autocalls, which are one of the most complex types of SRPs, have experienced higher growth rate than other products. Autocall sales accounted for only about 1% of all SRP in 2001 but that share increased steadily and was about 45% as of 2016. The same trend is observed in the United States, the biggest equity-linked SRP market, as seen in Figure 1, Panel B. Autocalls have experienced steady growth in the United States as well. I also present proportions of sales taken by other kinds of products, which I explain in detail in the next subsection. Reverse convertibles, which were once popular, have experienced a sharp decline in sales and participation products show a slow growth pattern. Understanding these patterns in the sales dynamics of various types of products is one of the main goals of this research.

2.2 Examples of SRPs

In what follows, I provide descriptions and examples of four types of SRPs, issued in the United States, which cover a broad range of products. Understanding these examples is important for understanding the empirical design of my research, which I explain in detail in the next section.

A. Capital-protected participation products

The first type of SRP I introduce here is capital-protected participation product presented in Figure 2, Panel A. A participation product is a relatively simple product in the sense that the return on the product at maturity is determined by the return of the underlying asset at maturity and the continuous trajectory of the performance of the underlying asset does not contribute to the return on the product at maturity.

[Insert Figure 2 here.]

One example of a capital-protected participation product, called *Principal Protected Product*, was issued by the Canadian Imperial Bank of Commerce in the United States on June 13, 2005, maturing on June 15, 2010. The underlying asset of this product is the S&P 500 index. As the name of the product indicates, the main feature of this product is that investors' principal (or capital) is protected irrespective of the performance of the S&P 500 index.

The return on this product at maturity is determined by the return on the S&P 500 index over the five-year investment period. For SRPs, returns on the underlying asset is measured based on the ex-dividend price of the underlying asset. More specifically, the underlying return is defined as $\frac{\text{Level of S\&P 500 on maturity date}}{\text{Level of S\&P 500 on issuance date}} - 1$. This product provides 70% of the underlying return at the maturity if the underlying return is greater than 0%. For example, if an investor invests \$100 on the issuance date and the underlying return is 10%, the investor receive \$107 at maturity. Otherwise, the investor receives the principal, \$100, irrespective of the size of any negative shock to the underlying asset. Therefore, the investor sacrifices 30% of the upside while his/her principal is fully protected in any case.

B. Non-capital-protected participation products

The second type of SRP is non-capital-protected participation product presented in Figure 2, Panel B. The name of this product is *Leveraged Bu ered Notes* and was issued by Goldman Sachs on April 22, 2014. This product is linked to the Eurostoxx 50 index for a two-year term. The payoff structure of this product is similar to that of the previous example with the main difference being that the capital is not fully protected. Investors enjoy 159% of the underlying return if the underlying return is positive. Their capital is protected until the underlying return reaches -15% and investors begin to lose capital at a rate of 1.1765% for every 1% fall in excess of -15%. Although investors enjoy a high participation rate (159%), they could lose the capital they invest in a bear market.

C. Reverse convertibles

The third example of an SRP is reverse convertible, which was once popular in the United States. This is known as one of the most typical types of SRPs. In Figure 2, Panel C I present an example of a reverse convertible issued by JP Morgan Chase on May 21, 2015, which was linked to the Linkedin stock price. The term of this product is one-year and investors earn 8.5% annualized coupons paid every quarter during the tenure of the product, which means that a 2.15% of coupon is paid every quarter. This coupon rate is quite high considering that this product was issued in a low-interest environment. Such a high coupon rate is generated by the special structure of the reverse convertible: a significant downside risk. If the underlying return has ever fallen below the knock-in barrier, -30%, during the investment period, investors receive only the underlying return at maturity. Otherwise, investors receive their full invested money back at maturity. The payoff structure around the knock-in barrier is similar to the short position of a put option. Intuitively, when an investor buys a reverse convertible, he/she effectively sells a put option to the issuer, and therefore the issuer can generate the high coupon rate using the put option.

D. Autocalls

The last SRP type I introduce here is the autocall. One example of an autocall, called *Autocallable Optimization Securities with Contingent Protection*, was issued by HSBC on March 26, 2008 with a term of 1.5 years. The underlying asset of this product is the S&P 500 index. The underlying return is the defined similarly, $\frac{\text{Level of S\&P 500 at time t}}{\text{Level of S\&P 500 on issuance date}} - 1$, but I use the time subscription t for the definition of the underlying return. Unlike what occurs with the participation products, the underlying return here is monitored quarterly to determine the redemption amount. The quarterly dates are called call dates. On the first call date, if the underlying return is greater than the knockout barrier, which is 0% in this example, 6% of the coupon along with the principal is paid to the investor and this product is terminated. I interpret this to mean that this product is automatically called by the issuer if a specified condition is met, which is why this product type is termed an *autocall*. If the product is not called because the underlying return is lower than the knockout barrier, then I check this condition on the second call date, which is six months after the issuance date. If the underlying return on the second call date is greater than the knockout barrier, 12% of the coupon along with the principal is paid and the product is terminated as on the first call date. The investor carries out this procedure again if the product is not automatically called on any call date because of low returns on call dates.

If an autocall fails to be automatically called by maturity, we need to determine whether the underlying return has ever fallen below the knock-in barrier, which is -50%, during the investment period. If it has ever fallen below the knock-in barrier, an investor receives only the underlying return at maturity. If the underlying return has never fallen below the knock-in barrier, the investor receives 36% over the term of the product (1.5 years). This translates to an annualized coupon rate of 24%. Such a high coupon rate can be provided because investors effectively sell put options to issuers on the issuance date as is the case with reverse convertible purchases.

2.3 Investor characteristics

Who buys SRPs? Unfortunately, to the best of my knowledge, there is no comprehensive study of SRP investors in major SRP markets. I utilize the results of a survey of 1,049 SRP investors conducted in August 2010 by the Financial Supervisory Service, a finance watchdog in South Korea, to provide a synopsis of investor characteristics. South Korea is the second biggest market next to the United States in terms of cumulative sales volume of equity-linked SRPs. Although the survey is confined to South Korea, I believe it nevertheless provides meaningful information pertaining to the characteristics of investors in major SRP markets. I summarize the detailed results of the survey in Appendix D.

The average age of respondents is 42 years and 81.4% report having earned a college degree.[3] The average current investment in SRPs is around $35,000. Although the average asset value is hard to calculate based on this the survey data, the median asset value is in the range of $100,000 - $500,000. Considering that the median asset value of households in Korea in 2010 was $140,000 (according to Statistics Korea), it seems that SRP investors do not hold more value in assets than the average household in Korea. Regarding risk preference, 66.7% of respondents consider themselves to be "risk-seeking" or "extremely risk-seeking." Their occupations are not particularly skewed to finance-related jobs since only 29.2% of them have such jobs. One of the most common reasons why investors purchase SRPs is because expected returns of SRPs are high. Overall, the SRP investors comprising the sample have higher education attainment levels than the average Korean are generally risk-seeking investors, but their other characteristics are not particularly different from the South Korean population as a whole.

3 Data and Empirical Design

3.1 Data

A. SRP data

In this study, I analyze equity linked-SRPs issued in the United States between 2001 and 2016. Equity linked-SRPs have stock market indexes or individual stocks as underlying assets. I obtain the sample of SRPs from Structured Retail Products, a data provider that specializes in the structured retail products industry. Conducting academic research on SRPs involves several challenges. The first challenge is that there is no publicly available database that includes all issued SRPs. The second challenge is that information pertaining to each SRP is available only in text format. Issuers of SRPs provide prospectuses that describe essential information about the SRPs to the public in text format.[4] However, because each issuer has its own forms for its prospectuses, it is impossible to extract essential information based on a simple technique. Due to these two bottlenecks, academic research on SRPs remains skimpy relative to research on other financial products.

[3] In 2010, the average college graduation rate in South Korea was about 40%.

[4] See Appendix A for an actual example of the prospectus of an *Autocallable Optimization Securities with Contingent Protection* product, offered by HSBC on March 26, 2008.

The data provider, Structured Retail Products, addresses these challenges by collecting prospectuses from multiple sources, including issuers themselves, and analyzing each prospectus. Through this procedure, the data provider has constructed the most comprehensive database on SRPs that covers all SRPs issued in all countries. An example of the format of the data is provided in Table 1.

[Insert Table 1 here.]

Following Célérier and Vallée (2017), among the SRPs that the database covers, I choose publicly available retail tranche-type products that are considered non-standardized SRPs. Other types of products, such as flow products, are standardized products and are usually traded on exchanges. Such products share similar characteristics with plain vanilla options.[5] Altogether, my sample consists of 71,300 with and total sales volume of $332.87 billion.

B. Market data

I use Bloomberg and CRSP as a source of market data for prices and dividend yields of underlying assets. To measure SRP markups and performance of SRPs, having data on exchange-traded options is essential. I obtain exchange-traded option data from Optionmetrics USA for options for individual stocks and indexes in the United States. I obtain credit default swap spread data from Markit to measure issuers' credit risk. Finally, to obtain market risk premiums for the S&P 500 index, I access the data calculated on an annual basis based on the free-cash-flow approach described in Damodaran (2018). The data are available on his website.[6]

3.2 Empirical Design

A. Complexity and extrapolation hypothesis

How do investors deal with financial complexity? Brunnermeier and Oehmke (2009) introduce several approaches that bounded rational investors can take to deal with financial complexity. First, investors divide complex products into several pieces that are relatively easy to analyze. Second, investors use "building blocks." For example, when making a decision to buy Goldman Sachs stocks, investors combine the stock price of Goldman Sachs, a building block, with his own private information rather than trying to conduct a full-fledged bottom-up valuation exercise. Finally,

[5] I also exclude call overwriting and warrant products because these are also considered standardized products. The proportion of these products is very small, and therefore excluding them does not change the main results of my analysis.

[6] Equity risk premium `http://pages.stern.nyu.edu/~adamodar/`

investors can use a simple model such as Black Scholes formula to understand complex financial products although such simple model doesn't fully capture complicated nature of reality.

It is worth noting that the three SRP examples that I introduced in the previous section except autocalls are easily analyzed using the above approaches. For example, the capital-protected participation product example in Section 2.2 is divided into a call option and a bond. Similarly, the non-capital-protected participation product example is decomposed into a call option, a short position in put option, and a bond. The reverse convertible example can be decomposed into a coupon bond and a short position in a knock-in put option, whose closed-form solution is available (Derman and Kani, 1997).

However, how can investors deal with complexity if none of the above approaches can be employed because the products are very complex? Autocalls are good examples of such products. It is known that autocalls cannot be decomposed into several pieces that are easy to analyze, and there is no building blocks to use. In addition, there does not exist a closed-form solution of the price for an autocall even under very simple pricing assumptions (Hansson, 2012).

I conjecture that investors might depend on extrapolative expectations in purchasing complex financial products, under which investors estimate expected returns of products based on past ex-post returns. Extrapolation has been studied extensively in behavioral finance (Amromin and Sharpe, 2009; Greenwood and Shleifer, 2014; Vissing-Jorgensen, 2003). Extrapolation has been successful in explaining various asset pricing puzzles and particularly successful in explaining behaviors of stock returns compared to other behavioral finance theories (Barberis, 2018). Since equity-linked SRPs have stock indexes or individual stocks as underlying assets, it is natural to conjecture that investors exhibit extrapolative extrapolations in the market for equity-linked SRPs. In addition, the tendency to rely on extrapolation might be stronger for more complex products because it is harder for investors to rely on other approaches to deal with complexities for those products. Taken together, I propose the following testable hypothesis, which I term *Extrapolation Hypothesis*.

Hypothesis (Extrapolation Hypothesis)

(i) Investors buy more SRPs that provided higher past returns.

(ii) Investors respond more aggressively to the past returns in purchasing more complex products.

B. Construction of group-level data

Testing the *Extrapolation Hypothesis* is challenging in the market for SRPs. SRPs are not standardized and a SRP is not issued repeatedly. Therefore, measuring the past return for a product, which is essential for testing the *Extrapolation Hypothesis* is impossible. To resolve this challenge, I categorize SRP products into several groups and construct "group-level data" at each time based on "product-level data."

First, I systematically categorize SRPs into five types using simple criteria, motivated by several benchmark categories including SEC.[7]

[Insert Figure 3 here.]

The most important criterion that I use to split the SRP product space into two groups is the *yield-enhancement property*. Products with the yield-enhancement property deliver high coupons relative to benchmark rates by exposing investors to the tail risk. Investors buying these products implicitly sell a type of put options to issuers and issuers offer high coupon rates in normal times through sales of the put options. The yield-enhancement products group is further subdivided into two groups based on *the xed maturity criterion*. Products with fixed maturities are called *reverse convertibles* and products with non-fixed maturities are called *autocalls*.

In the non-yield-enhancement products group, there are diverse product types and it is challenging to categorize them systematically. Therefore, I choose to introduce one criterion that defines a big product group called *participation products* and define the rest as *`Others'*. Participation products are products whose returns at their maturities are determined by underlying returns at maturities and do not depend on the intermediate underlying returns over the investment period. Participation products are divided further into two groups: capital-protected, and non-capital-protected participation products, depending on whether the investors' capital is protected in any case or not. The 'Others' product group is much smaller than other groups and, therefore, grouping them into one separate category does not significantly affect the main results.

I further divide each category into several groups based on underlying assets and construct the group-level variables at each time by taking the medians of the product-level variables. I present the detailed procedures in the next section.

[7]SEC. https://www.sec.gov/oiea/investor-alerts-bulletins/ib_structurednotes.html

4 Methodologies

4.1 Text mining for payoff structures

One of the bottlenecks in SRP research is that raw data are collected only in unstructured text format. This is particularly true in SRP markets, where the prospectuses that contain information on payoff descriptions of the products are provided by issuers in text formats. They are quite heterogeneous across issuers and across products. Fortunately, Structured Retail Products collects all prospectuses and summarizes the payoff descriptions in plain English, as seen in Table 1. The next challenge is to fully interpret payoff descriptions. Purely statistical learning-based approaches are prone to error, and more importantly, even if errors occur, it is hard to explain why such errors occur. In addition, analyzing each payoff description is unrealistic because of a large sample size, 71,300. In order to overcome this challenge, I take apply a simple and precise text mining technique to convert the payoff descriptions into a machine readable format, which I describe in Appendix B. Basically, I fully take advantage of a similar paragraph structure that describes payoff structures of the same type of SRPs. Using the text mining technique, I fully interpret a significant portion of the entire sample of products. Of the 71,300 entire sample of products, I fully interpret 67,861 product descriptions. The remaining 3,439 product descriptions were incomplete and could not be analyzed.

4.2 Construction of main variables

In this subsection, I explain how to construct main variables of interest: financial complexity, annualized realized return, markup, past return, and volatility. Estimating markup, past return, and volatility, requires making sophisticated modeling assumptions. More assumptions are needed for SRPS that have multiple underlying assets, and these estimations are heavily driven by the assumptions. Therefore, in this work, I exclude the SRPs that have multiple underlying assets and focus on SRPs that have a single underlying asset. I use full sample to estimate annualized realized returns because it requires no modeling assumptions.

4.2.1 Financial complexity

I construct three measures of financial complexity for SRPs. *Complexity (Autocall)* is a dummy variable that equals to 1 if an SRP is an autocall and 0 otherwise. This measure is proposed based on the idea that autocall is one of the most complex types of SRPs as discussed in Section 3.2. In order to define the two other complexity measures, I follow the approach used in Célérier and Vallée (2017). I define ***Complexity (# of scenarios)*** that counts number of scenarios in the description of a payoff structure of an SRP. This complexity measure captures the degree of complexity of conditional statements needed to describe the payoff structure. For example, ***Complexity (# of scenarios)*** of the capital protected participation product in Figure 2, Panel A is 2 because in the two different scenarios where underlying return is positive or negative, the payoff structures are different. By the same logic, ***Complexity (# of scenarios)*** of the non-capital protected participation product in Figure 2, Panel B is 3. Finally, I define ***Complexity (# of characters)*** as the number of characters that are used in payoff descriptions and the unit of this measure is 1,000 characters.[8] This measure is proposed based on the idea that more complex SRP is likely to need more characters to describe its complex payoff structure.

4.2.2 Annualized realized returns

I calculate annualized realized return by combining the text mining described in the previous section and market data on underlying assets. A typical SRP provides a stream of coupons on top of a redemption amount at maturity. In the spirit of the bond yields, I define the annualized realized return, r^{ARR}, for an SRP based on the following formula,

$$0 = -P + \frac{c_{T_1}}{(1+r^{ARR})^{T_1}} + \frac{c_{T_2}}{(1+r^{ARR})^{T_2}} + ... + \frac{c_{T_N} + X_{T_N}}{(1+r^{ARR})^{T_N}}, \tag{1}$$

where c_{T_i} represents intermediate coupon payments at time T_i, X_{T_N} is the redemption amount at maturity (T_N), and P is the price of the product. T_N is a fixed time for non-autocalls and it is a stopping time, a random variable that is a function of the performance of underlying assets, for autocalls. The solution of the above nonlinear equation is unique because c_{T_i} and X_{T_N} are nonnegative and the sign of the payoff stream changes only once when the first payment occurs. Therefore, r^{ARR} is a well-defined measure. After applying the text mining techniques to determine the stream of coupons (c_{T_i}) and the redemption amount (X_{T_N}), I solve the equation to obtain r^{ARR}.

[8]For autocalls, I also add the number of characters used in the ***Early redemption information*** part as in Table 1.

4.2.3 Markups

Estimating markup requires modeling assumptions regarding the dynamics of underlying assets. I employ the stochastic volatility model proposed by Heston (1993).[9] The stochastic volatility model is commonly used in practice in derivative pricing. It is proposed to explain anomalies generated from simple assumptions regarding the process of underlying assets and it is a good alternative for resolving the issues arising from simple pricing assumptions such as Geometric Brownian Motion (GBM). It assumes the following dynamics of the price (S_t) and variance (V_t) of an underlying asset under a risk-neutral measure, Q:

$$\begin{aligned} \frac{dS_t}{S_t} &= (r_f - q)dt + \sqrt{V_t}dW_t^1 \\ dV_t &= a(\bar{V} - V_t)dt + \eta\sqrt{V_t}dW_t^2 \\ dW_t^1 dW_t^2 &= \rho dt \end{aligned} \tag{2}$$

where r_f is the risk-free rate, q is the dividend yield, $\bar{V}$ is long-run variance, η is the volatility of V_t, and ρ is instantaneous correlation coefficient between variance and the underlying asset. I assume that the risk-free rate (r_f) and dividend yield (q) are constant over time. I use the yield of treasury bonds with the same term of the corresponding SRP to obtain the risk-free rate. For dividend yield (q), I use the implied dividend yield provided by Optionmetrics USA if it is available. If the implied dividend yield is unavailable and options are European style, I use put-call parity to find the implied dividend yield of options proposed by Binsbergen et al. (2012), as follows:

$$q = -\frac{1}{T}\log\left(\frac{C(K,T) - P(K,T) + Ke^{-r_f T}}{S_0}\right) \tag{3}$$

where $C(K,T)$ and $P(K,T)$ are the prices of the call and put options with the strike price and time to maturity, K and T, respectively. Most individual stocks options are American style and the implied dividend yield from Equation (3) is not valid since put-call parity does not hold for American options. In such a case, I calculate the dividend yield by dividing the 12-month trailing dividends of individual stocks by individual stock prices.

I first calibrate the model using available exchange-traded option data. Heston (1993) derives the closed-form solutions of European call options, $C^{Heston}(K,T;a,V_0,\bar{V},\eta,\rho)$, and they are pre-

[9] The seminal papers by Black and Scholes (1973) and Merton (1973) derive the price of call options under the assumption that prices follow Geometric Brownian Motion (GBM). The limitation of this approach is highlighted in many subsequent studies including Aït-Sahalia and Lo (1998). In particular, Geometric Brownian Motion (GBM) fails to explain the pattern of an implied volatility surface across different strike prices and maturities.

sented in Appendix C. I calibrate the stochastic volatility model for an underlying asset on each issuance date of a corresponding SRP by minimizing the following least square of the difference between market-implied volatility and implied volatility derived from the Heston model, denoted as σ^{Heston}:

$$(a^*, V_0^*, \bar{V}^*, \eta^*, \rho^*) = \underset{a, V_0, \bar{V}, \eta, \rho}{\arg\min} \frac{1}{N} \sum_i \left(\sigma^{Heston}\left(K_i, T_i; a, V_0, \bar{V}, \eta, \rho\right) - \sigma(K_i, T_i)\right)^2$$

where $\sigma(K_i, T_i)$ is the implied volatility of call options traded in secondary markets with strike price and time to maturity K_i and T_i, $\sigma^{Heston}\left(K_i, T_i; a, V_0, \bar{V}, \eta, \rho\right)$ is the implied volatility of the call option price derived from the Heston model with a given set of parameters, $(a, V_0, \bar{V}, \eta, \rho)$, and N is the number of options available in the market.

After I find the optimal set of parameters, $(a^*, V_0^*, \bar{V}^*, \eta^*, \rho^*)$, I generate 10,000 paths for the underlying asset price, S_t, from the stochastic volatility model at the optimal set of parameters. I employ an Euler Scheme to generate the prices by iterating the following two equations:

$$\begin{aligned} \log(S_{t+\Delta}) &= \log(S_t) + \left(r_f - q - \frac{1}{2}V_t\right)\Delta + \sqrt{V_t} Z_X \sqrt{\Delta} \\ V_{t+\Delta} &= V_t + a(\bar{V} - V_t)\Delta + \eta\sqrt{V_t} Z_V \sqrt{\Delta} \end{aligned}$$

where Z_X and Z_V are standardized Gaussian variables with correlation coefficient ρ and Δ is the time interval. I use $\Delta = \frac{1}{252}$ assuming that there are 252 trading days a year. I define markup and annualized markup as follows:

$$\begin{aligned} Markup &= \frac{P - FV_0}{P} \\ Annualized\ Markup &= \frac{1}{T}\left(\frac{P - FV_0}{P}\right) \end{aligned} \tag{4}$$

where P is the price of an SRP and FV_t is the fair value of an SRP at time t, with the following form:

$$FV_t = E_t^Q\left(\int_t^T e^{-r_f(s-t)} f(S_s) ds\right) \tag{5}$$

where f is the payoff function of an SRP. Here, subscript 0 in FV_0 indicates the issuance date.

4.2.4 Past returns

To test extrapolative expectations, measuring past returns on SRPs is essential. Because there are no secondary markets for SRPs in my sample, it is impossible to measure returns using historical prices. In addition, the varying lengths of terms across products make the direct use of annualized realized returns unreliable as a measure for past returns. To resolve this issue, I measure the fair value of a product, FV_t, at the end of every quarter. At the end of each quarter, t, I estimate the past return (r_t^{Past}) over the last one-year period, by solving the following equation for r_t^{Past}:

$$0 = -FV_{t-4\ quarters} + \frac{c_{T_1}^{Intermediate}}{(1+r_t^{Past})^{T_1}} + \frac{c_{T_2}^{Intermediate}}{(1+r_t^{Past})^{T_2}} + ... + \frac{c_{T_M}^{Intermediate} + FV_t}{(1+r_t^{Past})^{T_N}}. \tag{6}$$

where $c_{T_i}^{Intermediate}$ $(i = 1, 2, ..., M)$ is the coupon paid between (t-4 quarters, t] and FV_t and $FV_{t-4\ quarters}$ are calculated based on Equation (5). Intuitively, r_t^{Past} measures the holding period return between t-4 quarters and t, assuming that the market price at time, t, is the same as FV_t.

If the product matures in (t-1 quarter, t], I assume that the product matures at time, t. If the term of an SRP is not longer than one year, I use P, the price of an SRP at issuance, instead of $FV_{t-4\ quarters}$ in Equation (6). Then, Equation (6) reduces to Equation (1) and in that case, r_t^{Past} is equal to annualized realized return. r_t^{Past} is an important input to estimate *Past return* of a group of SRPs, which I explain in detail in Section 4.4.

To evaluate E_t^Q, I generally follow the approach for estimating markups described in the previous subsection. I use the stochastic volatility model calibrated at issuance and update the risk-free rate (r_f) and dividend yield (q) when I evaluate E_t^Q in each quarter t. If exchange-traded option data are not available for some underlying assets, I estimate historical volatility based on past one-year monthly returns on underlying assets and use GBM to generate sample paths of prices. I use a relatively short period for the data sample, one year, to estimate volatility to capture a short-term trend in volatility.

4.2.5 Volatility

I calculate the volatility of an SRP to measure its risk. Since there are no secondary markets for SRPs in our sample, it is impossible to estimate the volatility using historical returns. I take advantage of estimates for the volatility and the beta of underlying assets to resolve this issue. I estimate the volatility of SRPs linked to the S&P 500 index or individual stocks of the companies in the United States.

I estimate volatility for an underlying asset of an SRP on its issuance date by taking a standard deviation of the past three years of monthly returns. To estimate the beta for the underlying asset, I regress, excess returns on the underlying asset, defined as returns on the underlying asset minus the three-month treasury bill rate, on the contemporaneous excess market using the past three years monthly data.

I denote estimates for volatility and beta of underlying asset as $\hat{\sigma}$ and $\hat{\beta}$. To estimate the volatility and beta of an SRP, I generate 10,000 sample paths of the price of each underlying asset based on the following equation:

$$\frac{dS_t}{S_t} = (\hat{\mu} - q)dt + \hat{\sigma} dW_t. \tag{7}$$

where $\hat{\mu} = r_f + \hat{\beta}\ E(r_m - r_f)$ and q is dividend yield. For dividend yield q, I divide the 12-month trailing dividend of the underlying asset by the underlying asset price at issuance. I use the estimate for the market risk premium, $E(r_m - r_f)$, which is available on Damodaran's website.[10] I use the treasury bond yield with the term that closely matches the term of the SRP to obtain risk-free rate. For each sample path, I calculate annualized realized return using Equation (1). Finally, to estimate the volatility of an SRP, $\hat{\sigma}^{SRP}$, I take the standard deviation of the annualized realized returns calculated from each sample path.

4.3 Validity of text mining

I provide evidence that my text mining technique reliably extracts the full information on payoff structures by comparing the annualized realized returns on SRPs provided by the data provider, which does not cover entire sample, and my estimates obtained from the text mining technique.

[Insert Figure 4 here.]

Figure 4 is based on 7,411 products, a subset of the whole sample for which annualized realized returns are provided by the data provider.[11] The correlation coefficient is 0.97 and this high correlation is strong evidence that my text mining technique reliably extracts the full information on the products.

[10] http://pages.stern.nyu.edu/~adamodar/

[11] Here, I choose products that do not provide coupons during the investment periods because I find that the current data set from the data provider sometimes ignore coupon payments when calculating annualized realized returns.

4.4 Variables construction

I first define five types of SRPs for my main analysis according to Section 3.2 : capital-protected participation products, non-capital-protected participation products, reverse convertibles, autocalls, and others. I have 1,821 unique underlying assets in my sample period and I group them according to the following criteria. I group individual stock prices, based on the Bloomberg Industry Classification Standard (BICS). I group stock market indexes, based on countries. For example, the Nikkei 225 index and the TOPIX index are grouped into the *Japanese stock market index* group and KOSPI 200 and KOSDAQ are grouped into the *Korean stock market index* group.[12] At each time (t), I measure the variables of interest at underlying asset group (i) by product type level (j).

The main outcome variable is *Normalized sales*$_{i,j,t}$. *Normalized sales*$_{i,j,t}$ is defined as $\log\left(1+\frac{Sales_{i,j,t}}{Outstanding_{i,j,t-1}}\right)$, where $\text{Sales}_{i,j,t}$ is the aggregated sales volume for underlying group (i) and product type (j) at time t, and *Outstanding*$_{i,j,t-1}$ is the aggregated volume of SRPs with underlying group (i) and product type (j) that have not yet matured at time $t-1$.[13] I take log in order to guarantee that my result is not heavily driven by a few of outliers. This measure is analogous to the fund-flow measure in Chevalier and Ellison (1997).

Another important variable is *Past return*$_{i,j,t-1}$. To calculate this measure, I take the median of past returns (r^{Past}_{t-1}) on products with underlying group (i) and product type (j) at time $t-1$ by following the approach described in Section 4.2.3.

I also measure other variables for controls in a similar manner: *Annualized realized return*$_{i,j,t}$, *Annualized markup*$_{i,j,t}$, *Volatility*$_{i,j,t}$, *Sales commission*$_{i,j,t}$, *Term*$_{i,j,t}$, *One-year CDS spread*$_{i,j,t}$, *Complexity (Autocall)*$_{i,j,t}$, *Complexity (# of scenarios)*$_{i,j,t}$, and *Complexity (# of characters)*$_{i,j,t}$. These variables are defined similarly. I first measure *Annualized markup (%), Sales commission (%), Term (years), One year CDS spread (%), Complexity (Autocall), Complexity (# of scenarios), Complexity (# of characters) (in 1,000 characters)* and *Volatility (%)* at the product-level. After measuring these variables at the product-level, I take the median of the variables that have the same underlying group (i) and product type (j) and are issued at the same time t. I choose samples whose *Past return* information is available because this is the main explanatory variable. Finally, to prevent my results from being driven by very small SRPs, I further choose samples

[12] I make one exception here by separating the S&P, Russell, and NASDAQ indexes. These are all based on US stock prices but both are sufficiently large underlying assets. S&P indexes such as the S&P 500 and the S&P 100 are grouped into *S&P index* group and Russell indexes such as the Russell 2000 and the Russell 1000 are grouped into *Russell index* group. NASDAQ has only one index in my sample, the NASDAQ 100.

[13] If an SRP has more than one underlying asset and they are in different underlying groups, I assume that this product contributes $\frac{1}{\text{number of underlying assets}}$ of sales volume to *Sales* and *Outstanding* of each underlying group.

whose $\textit{Outstanding}_{i,j,t-1}$ is larger than \$35 million. Basic product-level and group-level summary statistics for my sample are presented in Table 2. The group-level data for my main analyses is measured at quarterly frequency.

[Insert Table 2 here.]

5 Extrapolation and Demand for SRPs

5.1 Ex-post performance of SRPs

As emphasized in Amy Starr's speech at the SEC (Starr, 2015), understanding the ex-post performance of SRPs is the first step toward understanding SRP market. Using the text mining technique described in Section 4.1, I construct annualized realized returns on 51,606 products. This is the largest sample ever studied and, most importantly, this sample should not be susceptible to any serious selection problem. The basic results are presented in Table 3.

[Insert Table 3 here.]

Since the beginning of the market, SRPs issued in the United States have provided on average 2.07% of returns with a standard deviation of 22.73%. The sales-volume-weighted average return is 3.28% with a sales-volume-weighted standard deviation of 18.99%. I use the sales volume-weighted performance results extensively hereafter to prevent my results from being potentially driven by small SRPs.

During the same sample periods, the one-year Bank (AAA) Bond has provided 3.7% of average returns with a standard deviation of 1.43% and the S&P 500 index has provided 6.39% of average returns with a standard deviation of 14.6%. Therefore, SRPs on average have provided worse performance than other simple benchmarks such as bond and stock market index.

It is worth noting that each type of SRPs has performed differently. Autocalls have provided 7.59% of average returns with a standard deviation of 13.44%. Non-capital-protected participation products have produced 4.00% of average returns with a standard deviation of 16.32% and capital-protected participation products have provided 3.3% of average returns with a standard deviation of 5.19%. Therefore, some product types such as autocalls have performed well, outperforming the the S&P 500 index in terms of average returns and standard deviations. Although it is difficult to compare the standard deviations of annualized realized returns of SRPs with the standard deviation of benchmark returns directly, I believe that such a comparison provides meaningful information.

Interestingly, the ex-post performance of reverse convertibles is under 0%. Reverse convertibles on average have provided -2.84% of returns with a standard deviation of 30.08% although such poor performance is driven mainly by products issued around the financial crisis. The poor performance of reverse convertibles is reflected in several litigation cases against issuers of reverse convertibles and special attention from the media.[14] Reverse convertibles have also been thoroughly studied in many academic papers and have served as typical examples of the "dark side of financial innovation" (Szymanowska et al., 2009; Wallmeier and Diethelm, 2008; Egan, 2019). In addition, the performance of 'other' type is also poor.

[Insert Figure 5 here.]

Figure 5 displays distribution of annualized realized returns for each type of SRPs. A notable feature is that reverse convertibles have a thick left tail compared with the other types. A significant portion of autocalls experienced gains and the left tail is thin. The distribution of non-capital-protected participation products looks relatively smooth compared with the other types. Beginning in the next subsection, I discuss extrapolative expectations in detail by investigating how past returns on SRPs explains higher sales volume.[15]

5.2 Extrapolation

In this subsection, I test the *Extrapolation Hypothesis* that I propose in Section 3.2.

[Insert Table 4 here.]

The main dependent variable is *Normalized sales* whose unit is %. As I show in the first column of Table 4, Panel A, there is a strong univariate relationship between *Past return* on SRPs and *Normalized sales*. Based on the coefficient, 0.264, seen in the first column, one-standard-deviation increase in *Past return* translates into a 4.14% increase of *Normalized sales*, where the standard deviation of *Normalized sales* is 19.4%. The positive relationship stays strong even after controlling for the underlying group and quarter fixed effects.

[14]FINRA Fines RBC $1.4 Million Over Unsuitable Reverse Convertibles. `https://www.securitieslawyersblog.com/finra-fines-rbc-1-4-million-over-unsuitable-reverse-convertibles/`

[15]Sources of the information on ex-post performance of SRPs vary across countries. Although investors can learn about the ex-post performance based on their own investments or by consulting with brokers, there are also publicly available sources of information. For example, in the United Kingdom, the UK Structured Products Association (UKSPA) keep track of all SRPs and provides monthly performance reports based on the ex-post performance of SRPs. Also, CompareStructuredProducts provides summary statistics of ex-post performance of SRPs.

To demonstrate the differential effects of extrapolation on sales of products with varying degree of complexity, I interact the three complexity measures, *Complexity (Autocall)*, *Complexity (# of scenarios)* and *Complexity (# of characters)*, with *Past return* in columns (3)-(8). The magnitude of the coefficient of the interaction term, 0.443, as seen in column (3), is sizable. This means that, for autocalls, which are considered one of the most complex types of SRPs, a one-standard-deviation increase in *Past return* translates into a 9.56% increase in *Normalized sales*. This effect stays strong even after controlling for underlying group and quarter fixed effects, as seen in column (4). I perform a similar exercise with the two other complexity measures, *Complexity (# of scenarios)* and *Complexity (# of characters)*. The coefficient of the interaction term, 0.071, that I report in column (5) implies that one-standard-deviation increase in *Complexity (# of scenarios)* translates into 4.3% increase in *Normalized sales* for every one-standard-deviation increase in *Past return*. Similarly, the coefficient of the interaction term, 0.564, in column (7) implies that having 1,000 more characters in the payoff descriptions translates into an 8.85% increase in *Normalized sales* for every one-standard-deviation increase in *Past return*. The results that I report in columns (6) and (8) indicate that controlling for underlying group and quarter fixed effects generally does not change the results.

The overall results remain generally unchanged even with more controls. As can be seen in Panel B of Table 4 I perform the same exercise with control variables: *Sales commission*, *Term*, and *One-year CDS spread*. My *Annualized markup* and *Volatility* data cover roughly 50% of the entire sample. Therefore, I provide results for regressions with control variables, including *Annualized markup* and *Volatility* separately in Panel C. The statistical and economic significance of these estimates for *Past return* $\times$ *Complexity*, which I report in Table 4, Panel B and Panel C, remain close to those reported in Table 4, Panel A.

In order to validate that investors' extrapolations persist over a long period of time, I run the same regression analysis on two subgroups of the full sample, split before and after December 31, 2012. I find that the results are similar to the results from the full dataset. This observation suggests that investors' extrapolations persist for this particular time period.

Overall, the results that I report are consistent with the *Extrapolation Hypothesis*. A similar phenomenon is well documented in other markets, such as mutual funds (Chevalier and Ellison, 1997; Sirri and Tufano, 1998). My results differ from results reported in previous literature on other markets insofar as investors depend on extrapolation when deciding whether to purchase *complex* financial products. More importantly, investors are more sensitive to past returns when they purchase more complex products. One possible interpretation of this phenomenon is that unsophisticated investors may chase high past returns on products and this effect is stronger when they buy more complex products because dealing with complexity of such products is harder and extrapolation becomes a more important influence on decision-making (Brunnermeier and Oehmke, 2009).

5.3 Extrapolation (Issuer level analysis)

Ideally, one would examine whether the returns on a product type experienced by a customer predict future purchases of the product type by the customer. Unfortunately, however, the necessary data are not available. To overcome this challenge, I exploit the idea that the matching between an issuer and a customer is likely to be stable because switching between different issuers could be costly. For example, a customer of Morgan Stanley is likely to remain a Morgan Stanley customer. If so, it could be hard for other issuers' SRPs to directly influence purchases by Morgan Stanley customers, because it is difficult for Morgan Stanley customers to know the returns on other issuers' SRPs unless the customers have additional accounts at other issuers. This suggests examining, for each issuer, the relation between lagged returns of the product type and future sales of the same product type. Lagged returns on a product type issued by Morgan Stanley capture the past experience of Morgan Stanley customers. Thus, they should predict future purchases of the product type by Morgan Stanley customers.

[Insert Table 5 here.]

In Table 5, I repeat the analysis of Table 4 by dis-aggregating the data at issuer level. Notably, the coefficient estimates of *Past return* and *Past return* $\times$ *Complexity* in Table 5 are qualitatively similar to those in Table 4 and remain statistically significant at 1-5% level, which provides further evidence supporting extrapolation by investors.

5.4 Extrapolation and financial advisers

A growing literature on the market for financial conducts emphasizes the role of financial advisers in retail investors' decision making processes (e.g. Egan et al., 2019; Egan et al., 2017; Egan, 2019) Therefore, it is natural to conjecture that financial advisers who want to deliberately exploit investors' extrapolation bias could only recommend SRPs that performed well in the past, which might drive the results.

Ideally, one would examine individual financial advisers' advice to retail investors. Unfortunately, however, the necessary data is not available and I exploit the following idea to mitigate the concern. Egan et al. (2019) document heterogeneity of the persistent financial misconducts across different firms and list top twenty firms with highest incidence of misconducts. If financial advisers in some firms exploit extrapolation bias and keep only recommending products with high past performance, they are more likely to get more complaints from investors because past performance do not predict future performance as will be seen in the next subsection. Therefore, if the results are mainly driven by financial advisers' misconducts, we should not observe the effect of extrapolation for products sold by firms whose misconduct rates are low. In the untabulated results of a sub-sample analysis excluding SRPs sold by twenty brokerage firms with highest incidence of misconducts reported in Egan et al. (2019), I find that the effect of extrapolation does not become weaker, which mitigates the concern that extrapolation is entirely driven by financial advisers' misconducts.

5.5 Extrapolation vs rational expectation

The strong relationship between *Normalized sales* and *Past return* discussed in previous subsections might be explained by rational expectation of retail investors. For example, if *Past return* contains information on returns of newly issued products with the same underlying group and same type, investors could demand more products that experienced high performance in the previous period and this explanation would be consistent with empirical patterns provided in previous subsections.

[Insert Table 6 here.]

In Table 6 I first present evidence confirming the relationship between annualized realized returns of newly issued products and *Past return*. The coefficients for *Past return* reported in columns (1) and (2) show that *Past return* does not explain the performance of newly issued products that have same underlying group and are of the same product type. I also study the relationship between annualized realized returns for newly issued products and *Normalized sales* and report the results in columns (3) and (4). The coefficients for *Normalized sales* are statistically insignificant, which implies that high *Normalized sales* is not correlated with better performance. Overall, my results rule out the possibility that investor decisions based on *Past return* are driven by rational information extraction.

5.6 Survey findings

In this subsection, I provide further evidence of investor extrapolation by introducing survey findings associated with SRP investors.

The first important finding that is common to the multiple surveys is that investors have only limited understanding of SRPs and their investment decisions are not based on careful evaluation of the risk-and-return profiles of these products. This result is consistent with my empirical finding that investors' decisions are not driven by rational information extraction from past returns on SRPs.

A 2006 survey conducted by the Securities and Futures Commission (SFC) in Hong Kong is based on 207 SRP investors. To measure their understanding of the SRPs in which they invested, investors were asked what would happen if the price of the underlying asset were to drop below the lower barrier beyond which investors lose part or all of their invested capital. To this question almost half of the investors gave a wrong answer as most them did not realize they could lose part or all of their investment capital in such an adverse scenario. More interestingly, 48.9% of investors recalled that they had received a prospectus for an SRP when they bought one. Also, only 10.7% of the investors responded that they had received and read and fully understood the document. Therefore, 89.3% of the investors either did not recall that they received a product prospectus or, even if they recalled receiving one, they did not read carefully or did not understand the details about the products in which they had invested.

Another survey was conducted in 2015 by Cha and Park (2015) with a sample of 336 SRP investors in South Korea. Investors were asked whether they understood the basic concepts related to SRPs: underlying assets, initial levels of underlying assets, volatility, knock-in barriers, and so on. Even though these concepts are essential to understanding the risks and returns associated with the products, investors on average answered that they understood 5.37 concepts out of 12 concepts. Similarly, Hunt et al. (2015) conducted a survey on 337 SRP investors in the United Kingdom in 2015. Investors were asked to answer questions about the basic concepts underlying SRPs. The proportion of correct answers ranged between 65% and 80% for most questions, but for some difficult question, the proportion of correct answers was only about 24%.

Other two surveys show that investors' past returns on SRPs are comparable to their expected returns of newly purchased SRPs, which is suggestive of extrapolation. In the survey conducted by Financial Supervisory Service (2010), investors were asked to provide the annualized realized returns on SRPs in which they invested in during the past two years and also about subjective expected returns on the products they invested in recently. The average of annualized realized returns over the past 2 years is 10% and average of subjective expected returns for newly issued products is around 13%, which is suggestive of extrapolative expectation. More evidence is provided by Cha and Park (2015). In this survey, the average of annualized realized returns of the products in which investors invested over a period of time preceding the survey is 13.4% and average of subjective expected returns for newly issued products is around 15.5%, which is suggestive of extrapolative expectation as well. Cha and Park (2015) divide investors into two groups based on the type of products they purchased: capital-protected-products and non-capital-protected products. Over 90% of the non-capital-protected products are autocalls in South Korea and capital-protected products are in general considered to be the simplest SRPs.

Caution is needed in interpreting the survey results because it is hard to establish a causal relationship solely based on survey results. However, I believe that my empirical results combined with the survey findings provide a useful starting point for understanding the role of extrapolative expectation in the market for complex financial products.

6 Extrapolation and Salient Thinking

While previous section describes strong evidence of extrapolation, it is natural to expect that SRP investors' decision making processes should be more complicated given the complex nature of SRPs. I conjecture that investors rely on multiple approaches to deal with financial complexities of SRPs and test two main hypotheses, extrapolation and investors' salient thinking, jointly in this section.

A seminal paper, Célérier and Vallée (2017), highlights the importance of investors' salient thinking as a main driver of sales of SRPs. SRP investors tend to be attracted by a salient feature of an SRP, called headline rate, which is shown in the first page of the prospectus, and make an investment decision mainly based on the headline rate. Since the headline rate is the maximum return that an SRP can generate when underlying asset performs well, one could argue that the results in the previous section could be driven by the headline rate rather than extrapolation.

[Insert Table 7 here.]

In Table 7 Panel A, I conduct a regression analysis to jointly test the hypotheses of extrapolation and salient thinking. In this analysis, I restrict the sample to reverse convertibles and autocalls because the other types of SRPs do not offer headline rates.[16] The magnitudes of the coefficient estimates for *Past return* are 0.228 - 0.383 depending on the specifications and are all statistically significant at 1% level.[17] Interestingly, the coefficient estimates for *Headline rate* are also positive and statistically significant at 1% level, which suggest that both investor salience and extrapolation are important in explaining the demand for SRPs. Furthermore, extrapolation and salient thinking do appear to be independent drivers that explain the demand for SRPs. In the untabulated result, I find that the correlation between *Past return* and *Headline rate* is -0.161. This small coefficient mitigates the concern that the effect of extrapolation could be subsumed by that of salient thinking and suggests that both of the two mechanisms are crucial in SRP investors' decision making processes.

Extrapolation and salient thinking are useful in explaining the dynamics of the SRP market. Along with the growing popularity of autocalls, another interesting pattern that we observe in this market is the fast declining pattern of reverse convertibles. (See Panel B in Figure 1.) First, this pattern is quite consistent with salient thinking. One could argue that autocalls could allow for very high headline rates because by its design, an autocall is likely to have a high probability of being called in a short term and therefore, the headline rate can be received for only a short period of time, which allows issuers to offer high headline rates on autocalls. Therefore, one could hypothesize that issuers figured out that autocalls are an efficient way to satisfy investor demand for high headline rates, and that this is the reason why autocalls replaced reverse convertibles during the sample period. Consistent with this prediction, Table 7 Panel B shows that the headline rates for autocalls are 1.8% higher than those of reverse convertibles after controlling for quarter and underlying group fixed effects. Since SRP investors tend to be attracted by high headline rates, higher headline rates offered by autocalls can explain the growing autocalls and declining reverse convertibles.

Second, extrapolation contributes additionally to the growth of autocalls and the decline of reverse convertibles. I report the sales-volume-weighted average of annualized realized returns on each type of SRP matured in each year in Table 3, Panel C. Autocalls have consistently outperformed reverse convertibles products in general over the sample period and this pattern becomes

[16] For example, in Figure 2, it is easy to observe that capital-protected and non-capital-protected participation products do not have headline rates whereas the reverse convertible and the autocall example products provide 8.5% and 24% or annualized headline rates, respectively.

[17] The coefficients are a bit larger than those in columns (1) and (2) of Panel A-C in Table 4. This is because the proportion of autocalls in Table 7 is larger than that in Table 4 and the effect of extrapolation is stronger in autocalls than in other products as described in Section 5.2.

modest from 2014. This further explains the rise and fall of autocalls and reverse convertibles because investors tend to extrapolate the past returns and this tendency is stronger for more complex products like autocalls. Extrapolation appears to be also useful in explaining sales patterns of the other types of products. The poor ex-post performance of 'others' explains the sharp declines of the market shares of those products, as seen in Figure 1, Panel B. The modest performance of participation products is also consistent with the modest growth of this product type.

Overall, stronger extrapolation for more complex products and salient thinking, combined with better ex-post performance and higher headline rates of more complex products, provide a clear explanation of the increasing complexity. The rapidly growing popularity of more complex products eventually contributes to the rapid growth of the overall SRP market.

6.1 Discussions on other potential mechanisms

6.1.1 Insurance demand by banks

As explained in Section 2.2, investors effectively sell put options to banks when purchasing autocalls. Therefore, it is possible that the growth of the autocalls might have been driven by insurance demand by banks to hedge their portfolio risks. However, this alternative explanation does not clearly explain the collapse of reverse convertibles. Banks can also secure put options by selling reverse convertibles. In addition, reverse convertibles are simpler products than autocalls because they do not have early termination properties, which allows banks to secure put options more easily by selling reverse convertibles than autocalls. Therefore, the salient opposite patterns of sales of reverse convertibles and autocalls are hard to be explained by the insurance demand by banks.

6.1.2 Hedging demand by investors

Investor demand for hedging offers another possible explanation. Investors might have purchased autocalls to hedge their portfolio risks. However, the evidence from the surveys of SRP investors conducted by Financial Supervisory Service in South Korea (Financial Supervisory Service, 2010) is inconsistent with the hedging demand hypothesis. In response to question 10 of the survey, which asks about investors' risk appetite, 66.7% of investors responded that they are "risk-seeking" or "extremely risk-seeking." In addition, in question 14, respondents were asked about the main reason for which they buy SRPs. The proportion of "others" (1.7%), which includes hedging purpose is quite small. We see similar results from the other surveys. In the survey conducted by the Securities and Futures Commission in Hong Kong (Securities and Futures Commission, 2006), the proportion of answers that are related to hedging demand is also low (4.4%). Overall, it is hard to explain that the investors buy complex products to hedge their portfolio positions.

7 Increasing Competition and Improved Transparency

7.1 Decreasing markup and increasing competition

A natural follow-up question is how financial intermediaries react in the presence of investor extrapolation. It is possible that this market remains "dark" and investors have been consistently exploited over time as highlighted in many early studies or this market might have become more competitive and such exploitation is not as strong as before. In this subsection, I provide evidence that markups of SRPs have consistently decreased and the competition between issuers has increased. This evidence suggests that exploitation through charging high markups has been getting weaker.

[Insert Figure 7 here.]

In Figure 7, I show how the median of annualized markups of SRPs evolves over time. To construct this figure, I choose S&P 500-linked SRPs because the S&P 500 is the most popular underlying asset for SRPs in the United States, and therefore many SRPs have been issued for a long time, which enables me to construct a long time series of median of annualized markups. In addition, option market for S&P 500 is quite liquid compared to others, and therefore S&P 500 options provide reliable volatility surface information, which reduces the estimation errors. I also restrict my sample to SRPs with terms of less than five years. The sample size for this figure is 7,117. For the markup estimation, I do not consider the credit risk. Therefore, the estimated markup measures issuers' profits per dollar invested in SRPs conditional on their having not defaulted.

The median annualized markup in 2004 was 1.9%, which means that products with one-year (three-year) term of maturity charged a markup of 1.9% (5.7%) in 2004. Such a high markup is consistent with findings from the early studies highlighting high markups in the SRP market (Henderson and Pearson, 2011; Stoimenov and Wilkens, 2005). In 2004, six issuers issued S&P 500-linked SRPs. The annualized markup and the number of issuers experienced significant change during 2004 - 2016. The annualized markup decreased after 2004 while number of issuers increased.

As of 2016, the average annualized markup was 0.46% and number of issuers was 16.[18] Overall, the time series patterns of markups and number of issuers show that the market gets competitive and taking advantage of investors by charging high markups is getting more difficult. I see the similar patterns using different measures such as weighted average instead of median, and therefore this result is robust. This result is consistent with the recent papers on markups on SRPs issued by members of Deutscher Derivate Verband (Deutscher Derivate Verband, 2015; Muller et al., 2017), which find that markups of SRPs issued by members of Deutscher Derivate Verband in 2013 (2016) are just about 0.36% (0.7%) on average and explain that such low markups are consistent with improved transparency and competition in the market for SRPs.

It is important to note that markups estimated from financial engineering models are generally overestimate actual profits that banks earn in selling SRPs. In estimating markup, financial engineering models assume that issuers do not affect the prices of derivatives when hedging their positions. However, there is ample evidence that risk exposure generated by SRPs is large. It is known that a few of large issuers account for a significant portion of this market and therefore, they sometimes suffer losses when they should take very big positions in derivative markets to hedge their positions because prices move against them (Cameron, 2013; Credit Suisse Equity Derivative Strategy, 2013; Credit Suisse Equity Derivative Strategy, 2014). Therefore, a high markup estimated from a financial engineering model does not necessarily imply that issuers earn high profits because a significant portion of the markup can be used for hedging cost.

7.2 Improved transparency - availability of accurate markup

Markup is known as "hidden price" because it is not observable but should be estimated using complex financial models. In this subsection, I show that the market has become more transparent in the sense that issuers have provided accurate information on markup since 2013, and therefore investors can easily access to this valuable information when they make a purchase decision.

In April 2012, the SEC Division of Corporate Finance Office of Capital Market Trends disseminated a letter to major issuers of SRPs. This letter was related to issues regarding disclosure of information in SRP prospectuses. Although there are several issues regarding disclosure, this letter primarily discussed about providing fair values of SRPs in prospectuses. Markups and annualized markups are directly calculated using fair values based on Equation (4). However, issuers were free

[18]When measuring number of issuers, I ignored very tiny issuers that issue less than 0.5% of market share in each year.

to use their own internal pricing models and assumptions regarding inputs because they are not required to provide detailed information on such inputs. Therefore, issuers could have provided inaccurate information on fair values.

To test if issuers provide reliable information on fair values, I compare annualized markups calculated based on the reported fair values with annualized markups estimated using the stochastic volatility model of Heston (1993). Similar exercises have been utilized in other papers in other settings with different samples, including Bauer et al. (2016) and Vokata (2018). My result differs from others in the sense that (i) my estimation error is smaller, and also (ii) the correlation between two markups is very strong, providing correspondingly strong evidence that banks provided accurate information on fair values.

[Insert Figure 6 here.]

The scatter plot displayed in Figure 6 shows the relationship between reported annualized markups and annualized markups estimated using the Heston model. The plot is drawn based on S&P 500-linked products that have maturities shorter than the five years. I choose S&P 500-linked products specifically because, again, S&P 500 options market is quite liquid compared to others, and therefore S&P 500 options provide reliable volatility surface information, which reduces estimation errors. I also choose products whose terms are shorter than five years to reduce estimation errors. When pricing products with very long maturity, assumptions put in the Heston model can significantly affect fair values. The correlation between the two annualized markups is 0.72. The OLS equation is as follows (N = 3,563):

$$\text{Annualized markup from Heston (\%)} = \underset{(0.021)}{-\,0.553} + \underset{(0.016)}{0.998} \times \text{Reported annualized markup (\%)}$$

where standard errors for the coefficients are presented in parentheses. The slope coefficient is not different from 1 at 5% significance level.[19]

[19]In this analysis, I do not control for issuers' credit risk. To control credit risk, I use CDS spreads of issuers, with term of two years, which is close the median of the terms of S&P 500-linked SRPs. Rather than discounting the payoffs with risk-free rate, I discount payoffs with risk-free rate + two-years term CDS spreads of issuers, as in Hull (2011), under a risk neutral measure. After controlling for credit risk, I obtain the following OLS equation:

$$\text{Annualized markup from Heston (\%)} = \underset{(0.023)}{0.029} + \underset{(0.017)}{0.992} \quad \text{Reported annualized markup (\%)}$$

where standard errors for the coefficients are presented in parentheses. The coefficient of the intercept is not different from 0 at the 5% level significance and the coefficient of the slope is not different from 1 at the 5% level significance.

Multiple explanations can support this phenomenon. For example, the competition between banks might curb the incentive to provide inaccurate information. This explanation is consistent with literature studying the effect of competition on analyst forecasting bias (Hong and Kacperczyk, 2010) and financial misreporting by managers (Balakrishnan and Cohen, 2013). Given that the issuers of SRPs are well-known global financial institutions that have operated over a long period of time and the number of issuers has been steadily increasing, the reputation concern and competition are consistent with the strong correlation pattern. Overall, investors have obtained this valuable information at no cost and this is suggestive of improved transparency.

7.3 Effect of extrapolation on markup and sales commission

In the presence of the extrapolative expectation, issuers (brokers) could charge higher markups (sales commission) for the products that provided high past returns to take advantage of extrapolation bias. In this subsection, I show that issuers (brokers) actually charge slightly lower markups (sales commissions).

[Insert Table 8 here.]

In Table 8, I report results indicating how *Past return* affects changes in annualized markups and sales commissions. More specifically, Table 8, Panel A and Panel B show the results of the following regressions.[20]

$$\Delta \textit{Annualized markup}_{k,m,i,j,t} = \beta \textit{Past return}_{i,j,t-1} + \gamma X_{i,j,t-1} + \epsilon_{i,j,t} \tag{8}$$

$$\Delta \textit{Sales commission}_{k,m,i,j,t} = \beta \textit{Past return}_{i,j,t-1} + \gamma X_{i,j,t-1} + \epsilon_{i,j,t} \tag{9}$$

where k is underlying asset, m is the term of SRPs[21], i is the underlying asset group, j is the product type and t is time. $\textit{Past return}_{i,j,t}$ is the past return of SRPs at time t and is defined by product type (j) at the underlying asset group (i) level, as explained in Section 4.4. To measure $\Delta \textit{Annualized markup}_{k,m,i,j,t}$ and, I calculate the difference between medians of the annualized markups of products that have the same term (m) and same underlying asset (k) issued at $t-1$ and t. Underlying asset (k) is a member of underlying asset group (i). I measure

[20] I do not find a clear result based on data at quarterly frequency. This is perhaps because issuers and brokers do not change markups or sales commissions very quickly and, even if they change them, the magnitudes of the changes might be small, and therefore hard to detect.

[21] Terms of SRPs are continuous and I round them to make them discrete.

Δ*Sales commission*$_{k,m,i,j,t}$ in similar fashion. As one of the control variables, I use *Past outstanding*, which is defined as *Outstanding*$_{i,j,t-1}$ (unit : \$ billion). In both panels, I provide the results of unweighted and sales-volume-weighted regressions to show that my results are not driven by small SRPs.

In Panel A, I show in columns (1) and (3) that *Past return* is negatively related to Δ*Annualized markup*. The result reported in column (3), implies that a one-standard-deviation increase in *Past return* translates into a 0.29% decrease in Δ*Annualized markup*. In columns (2) and (4) I show the results with interaction terms. The coefficients for *Complexity (Autocall)* $\times$ *Past return* and *Past outstanding* $\times$ *Past return* are positive. This implies that for more complex products and products of higher *Past outstanding*, the negative relation between Δ*Annualized markup* and *Past return* is weaker.

In Panel B, I show in columns (1) and (3) that *Past return* is weakly and negatively related to Δ*Sales commission*. As seen in columns (2) and (4), the coefficients for *Complexity (Autocall)* $\times$ *Past return* and *Past outstanding* $\times$ *Past return* are negative, which means that for more complex products and products with higher *Past outstanding*, the negative relationship between Δ*Annualized markup* and *Past return* is stronger. However, the magnitude of the coefficient is small and it is hard to tell whether the effect on Δ*Sales commission* is economically significant.

Overall, the annualized markups and sales commissions of products that enjoyed high returns in the past tend to decrease slightly although demand for such products increases due to investors' extrapolative expectations. I suggest several explanations of this phenomenon. First, the competition between issuers for products with high past returns might have intensified. Unfortunately, it is hard to measure competition very precisely with my current data at product-level. Brokers typically contact multiple issuers to request issuance of particular types of products. Multiple issuers then compete with each other to provide a given product at a lower price. Our data do not contain information about those issuers who take part in the competition and, therefore precise measurement of competition at product-level is challenging. Second, the elasticity of demand by marginal investors of products that provided high past returns might have increased and therefore, markup could have decreased.[22] Due to a lack of available data, I am unable to fully pin down the mechanism that would explain lowered annualized markups and sales commission for products that experienced high past returns. I leave this question for future research.

The positive coefficients of the interaction terms reported in columns (2) and (4) are worth

[22] In standard oligopolistic competition model, $\frac{Price}{Marginalcost} = \left(1 \quad \frac{1}{\epsilon}\right)^{-1}$ where ϵ is elasticity of demand.

noting. This result can be explained by the hedging cost that issuers face when hedging complex financial products. It is documented that issuers face high hedging costs when hedging complex SRPs such as autocalls and hedging costs rise even higher when the outstanding volume of SRPs is large (Credit Suisse Equity Derivative Strategy, 2013; Credit Suisse Equity Derivative Strategy, 2014). Because of the complex nature of the products, autocalls need to be dynamically hedged and in this process issuers face high hedging costs if the market for underlying, volatility or dividend is not liquid enough. Due to high hedging costs, issuers sometimes experience significant losses when hedging (Cameron, 2013). A recent scandal about Natixis is another good example.[23] Natixis, a well-known French issuer of autocalls, experienced $296 million because it failed hedging autocalls. A recent paper, Auh and Cho (2019), finds strong evidence that hedging autocalls generates about -10% abnormal return in the underlying asset when the autocalls are knocked-in, which leads them to conclude that typical assumptions of derivative pricing are violated in the SRP market and therefore, pricing and hedging SRPs are very challenging even for sophisticated issuers.

The positive coefficient of *Complexity (Autocall)* × *Past return* is consistent with higher hedging cost for autocalls than for other products. Although issuers charge lower annualized markups on average if *Past return* is high, issuers cannot lower annualized markups for autocalls because hedging costs are higher for autocalls. The positive coefficient of *Past outstanding* × *Past return* further strengthens my argument because as *Past outstanding* increases, issuers face stronger hedging pressures. Interestingly, the coefficients of interaction terms are not positive for changes of sales commission regressions, in Panel B. This may be because brokers do not face hedging pressures because their role is confined to marketing SRPs engineered by issuers without having any exposure to equity and derivative markets.

Overall, the negative relationship of annualized markups and sales commissions with past returns shows that financial intermediaries do not sell products that experienced high past returns more expensively although this effect is weaker for very complex products.

8 Conclusion

This is the first study that uses a comprehensive data set associated with complex financial products and investigates the role of investors' extrapolative expectations in understanding the rapid growth in sales volume and complexity for the SRP market. Sales volumes of the SRPs that

[23] https://www.bloomberg.com/news/articles/2018-12-18/natixis-suffers-114-million-revenue-hit-from-asia-trading-hedge

provided higher past returns increase faster due to extrapolation. Importantly, the effects of extrapolation are stronger for more complex products, which provides important clues for understanding the rapid growth in sales volume and complexity of the market.

Understanding how investors form beliefs is crucial in designing and implementing new regulations that apply to complex finanical products. In addition to implementing rules for the disclosure of the fair values of SRPs, regulators have focused on how to make prospectuses more transparent to convey information more effectively. However, improved market transparency through the enhanced disclosure alone may not be sufficient to prevent investor extrapolation as my analysis shows that even after the implementation of the SEC disclosure rule in 2013, extrapolation persists.

Although I find evidence that it is becoming more difficult for financial intermediaries to easily exploit investors' extrapolative expectations because the market has become more competitive and transparent, understanding how such extrapolation affects overall investor welfare is not clear yet. I leave this important question for future research.

References

Aït-Sahalia, Yacine and Andrew W Lo, "Nonparametric Estimation of State-price Densities Implicit in Financial Asset Prices," *Journal of Finance*, 1998, *53* (2), 499–547.

Allen, Franklin and Douglas Gale, *Financial Innovation and Risk Sharing*, MIT press, 1994.

Amromin, Gene and Steven A Sharpe, "Expectations of Risk and Return Among Household Investors: Are Their Sharpe Ratios Countercyclical?," *Working paper*, 2009.

Arnold, Marc, Dustin Robert Schuette, and Alexander F Wagner, "Neglected Risk in Financial Innovation: Evidence from Structured Product Counterparty Exposure," *Working paper*, 2018.

Auh, Jun Kyung and Wonho Cho, "Uncoordinated Hedging and Price Chain Reaction," *Working paper*, 2019.

Balakrishnan, Karthik and Daniel A Cohen, "Competition and Financial Accounting Misreporting," *Working paper*, 2013.

Barberis, Nicholas C., "Psychology-Based Models of Asset Prices and Trading Volume," *Working paper*, 2018.

Bauer, Janis, Holger Fink, and Eva Stoller, "Are Gross Margins of Structured Products Priced in a Market-Consistent Way? Evidence From the New Issuer Estimated Value," *Working paper*, 2016.

Binsbergen, Jules, Michael Brandt, and Ralph Koijen, "On the Timing and Pricing of Dividends," *American Economic Review*, 2012, *102* (4), 1596–1618.

Black, Fischer and Myron Scholes, "The Pricing of Options and Corporate Liabilities," *Journal of Political Economy*, 1973, *81* (3), 637–654.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, "Competition for Attention," *Review of Economic Studies*, 2015, *83* (2), 481–513.

Brunnermeier, Markus and Martin Oehmke, "Complexity in Financial Markets," *Working paper*, 2009.

Calvet, Laurent, Claire Célérier, Paolo Sodini, and Boris Vallée, "Can Financial Innovation Solve Household Reluctance to Take Risk," *Working paper*, 2017.

Cameron, Matt, "Uridashi Losses Put at 500 Million Dollars after Nikkei Rebounds," *Risk.Net*, 2013.

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

_ **and Gustavo Manso**, "Obfuscation, Learning, and the Evolution of Investor Sophistication," *Review of Financial Studies*, 2010, *24* (3), 754–785.

Célérier, Claire and Boris Vallée, "Catering to Investors through Security Design: Headline Rate and Complexity," *Quarterly Journal of Economics*, 2017, *132* (3), 1469–1508.

Cha, Kyung-Wook and Joo hyun Park, "Analysis of ELS Investment Behavior and ELS Types: Principal Guaranteed vs. Non-Guaranteed ELS (in Korean)," *Journal of Consumer Studies,*, 2015, *28* (2), 227–250.

Chevalier, Judith and Glenn Ellison, "Risk Taking by Mutual Funds as a Response to Incentives," *Journal of Political Economy*, 1997, *105* (6), 1167–1200.

Coval, Joshua, Jakub Jurek, and Erik Stafford, "The Economics of Structured Finance," *Journal of Economic Perspectives*, 2009, *23* (1), 3–25.

Credit Suisse Equity Derivative Strategy, "Systematic Trading Strategies: Extracting The Dividend Risk Premium," *Credit Suisse*, 2013.

_ , "European Equity Volatility Outlook: The Mighty European Autocall Market," *Credit Suisse*, 2014.

Damodaran, Aswath, "Equity Risk Premiums (ERP): Determinants, Estimation and Implications — The 2018 Edition," *Working paper*, 2018.

Derman, Emanuel and Iraj Kani, "The Ins and Outs of Barrier Options: Part 2," *Derivatives Quarterly*, 1997, *3*, 73–80.

Deutscher Derivate Verband, "Are Structured Products Too Expensive? : Facts and Figures," *Working paper*, 2015.

Döhrer, Björn, Lutz Johanning, Nils Steiner, and Arndt Völkle, "Issuer Margins for Structured Products in Germany," *Working paper*, 2013.

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

Egan, Mark, "Brokers versus Retail Investors: Conflicting Interests and Dominated Products," *Journal of Finance*, 2019, *74* (3), 1217–1260.

_ , Gregor Matvos, and Amit Seru, "The Market for Financial Adviser Misconduct," *Journal of Political Economy*, 2019, *127* (1), 233–295.

Egan, Mark L, Gregor Matvos, and Amit Seru, "When Harry Fired Sally: The Double Standard in Punishing Misconduct," *Working paper*, 2017.

Financial Supervisory Service, "A Survey on ELS Investors," 2010.

Gabaix, Xavier and David Laibson, "Shrouded Attributes, Consumer myopia, and Information Suppression in Competitive Markets," *Quarterly Journal of Economics*, 2006, *121* (2), 505–540.

Gennaioli, Nicola, Andrei Shleifer, and Robert Vishny, "Neglected Risks, Financial Innovation, and Financial Fragility," *Journal of Financial Economics*, 2012, *104* (3), 452–468.

Ghent, Andra C, Walter N Torous, and Rossen Valkanov, "Complexity in Structured Finance," *Review of Economic Studies*, 2017, pp. 1–29.

Greenwood, Robin and Andrei Shleifer, "Expectations of Returns and Expected Returns," *Review of Financial Studies*, 2014, *27* (3), 714–746.

Hansson, Fredrik, "A Pricing and Performance Study on Auto-callable Structured Products," 2012.

Henderson, Brian J and Neil D Pearson, "The Dark Side of Financial Innovation: A Case Study of the Pricing of a Retail Financial Product," *Journal of Financial Economics*, 2011, *100* (2), 227–247.

_ , _ , and Li Wang, "New Evidence on the Financialization of Commodity Markets," *Review of Financial Studies*, 2015, *28* (5), 1285–1311.

_ , _ , and _ , “Pre-trade Hedging: Evidence from the Issuance of Retail Structured Products,” *Journal of Financial Economics*, 2020.

Heston, Steven L, “A Closed-Form Solution for Options with Stochastic Volatility with Applications to Bond and Currency Options,” *Review of Financial Studies*, 1993, *6* (2), 327–343.

Hong, Harrison and Marcin Kacperczyk, “Competition and Bias,” *Quarterly Journal of Economics*, 2010, *125* (4), 1683–1725.

Hull, John C., *Option, Futures and Other Derivatives, 8th edition*, Prentice-Hall, 2011.

Hunt, Stefan, Neil Stewart, and Redis Zaliauskas, “Two Plus Two Makes Five? Survey Evidence that Investors Overvalue Structured Deposits,” *Working paper*, 2015.

Merton, Robert C, “Theory of Rational Option Pricing,” *Bell Journal of Economics and Management Science*, 1973, pp. 141–183.

Muller, Sigrid, Lutz Johanning, Christian Koziol, Dirk Schiereck, and Bernd Rudolph, “Total Costs and Cost Components of Investment in Retail Structured Products,” *Working paper*, 2017.

Securities and Futures Commission, “Structured Product Investor Survey,” 2006.

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

Sirri, Erik R and Peter Tufano, “Costly Search and Mutual Fund Flows,” *Journal of Finance*, 1998, *53* (5), 1589–1622.

Starr, Amy M., “Structured Products - Complexity and Disclosure - Do Retail Investors Really Understand What They are Buying and What the Risks Are?,” *U.S. Security and Exchange Commission*, 2015.

Stoimenov, Pavel A and Sascha Wilkens, “Are Structured Products ‘Fairly’ Priced? An Analysis of the German Market for Equity-Linked Instruments,” *Journal of Banking and Finance*, 2005, *29* (12), 2971–2993.

Szymanowska, Marta, Jenke Ter Horst, and Chris Veld, “Reverse Convertible Bonds Analyzed,” *Journal of Futures Markets*, 2009, *29* (10), 895–919.

Vissing-Jorgensen, Annette, "Perspectives on Behavioral Finance: Does Irrationality Disappear with Wealth? Evidence from Expectations and Actions," *NBER Macroeconomics Annual*, 2003, *18*, 139–194.

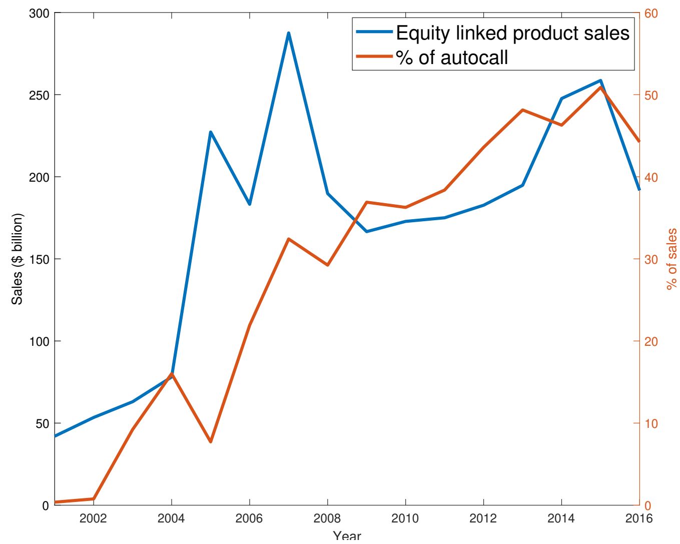
Vokata, Petra, "Engineering Lemons," *Working paper*, 2018.

Wallmeier, Martin and Martin Diethelm, "Market Pricing of Exotic Structured Products: The Case of Multi-Asset Barrier Reverse Convertibles in Switzerland," *Working paper*, 2008.

Figure 1: Sales dynamics of SRPs

These figures display the sales dynamics of the SRP market. In Panel A, I plot the sales dynamics of the SRP market based on all equity-linked SRPs issued in all countries. The blue line plots the annual sales volume of equity-linked SRPs. The red line plots the proportion of the annual sales of equity-linked autocalls compared with the annual sales of equity-linked SRPs. Panel B plots the sales dynamics of the SRP market based on SRPs issued in the United States. The blue line plots the annual sales volume of equity-linked SRPs. The red line plots the proportion of the annual sales of equity-linked autocalls compared to the annual sales of equity-linked SRPs. The red dashed (dotted) line plots the proportion of the annual sales of equity-linked reverse convertibles (participation products) compared with the annual sales of equity-linked SRPs. The red dotted line with a marker plots the proportion of the annual sales of 'others' equity-linked products compared with that of equity-linked SRPs. The units along the x axis are years and the units along the left (right) y axis are $ billions (%).

Panel A. Global trends of sales of SRPs



Panel B. Trends of sales of SRPs in the United States

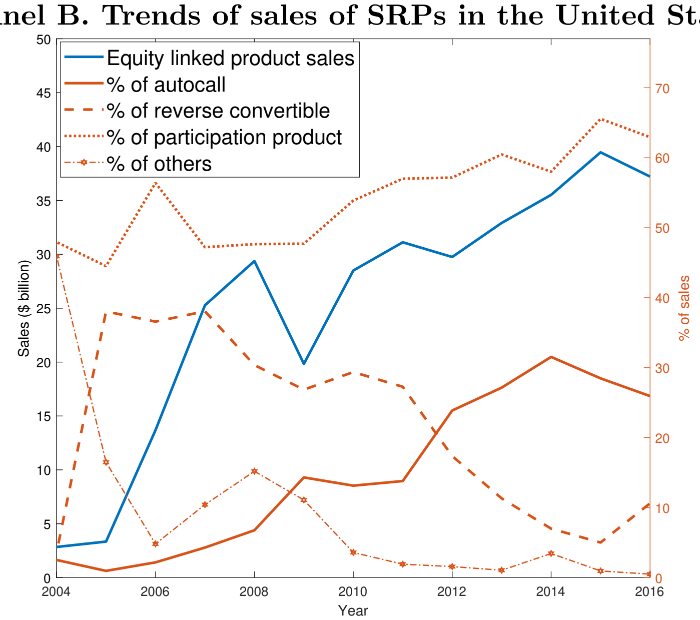
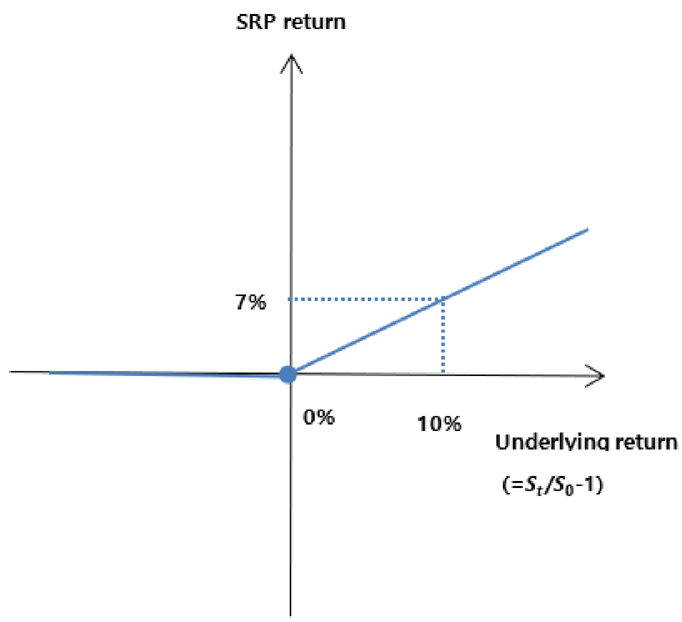


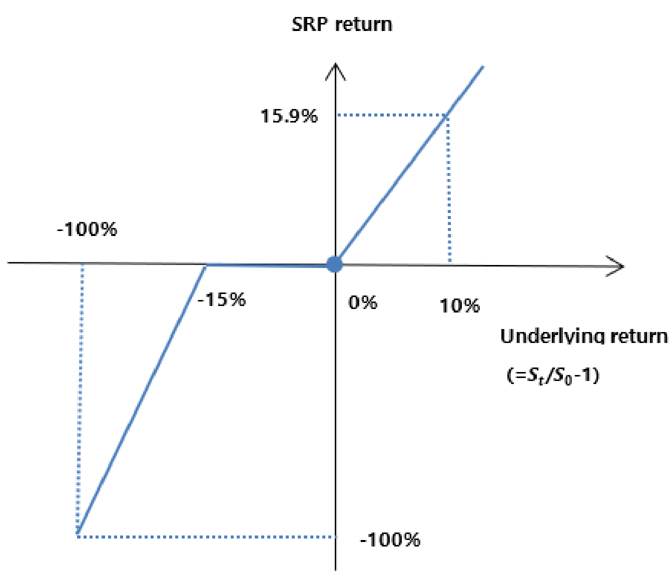
Figure 2: Examples of SRPs

The following figures display four real-world examples of SRPs. Panel A represents an example of a capital-protected-participation product linked to the S&P 500. This product was issued by the Canadian Imperial Bank of Commerce on June 13, 2005 with a five-year term. Panel B represents an example of a non-capital-protected participation product linked to the Eurostoxx 50. This product was issued by Goldman Sachs on April 22, 2014 with a two-year term. Panel C represents an example of a reverse convertible linked to the Linkedin stock. This product was issued by JP Morgan Chase on May 21, 2015 with one-year term. Panel D features and an example of an autocall linked to the S&P 500. This product was issued by HSBC on March 26, 2008 with a 1.5-year term. The characteristics of the product examples are described in detail in Section 2.2.

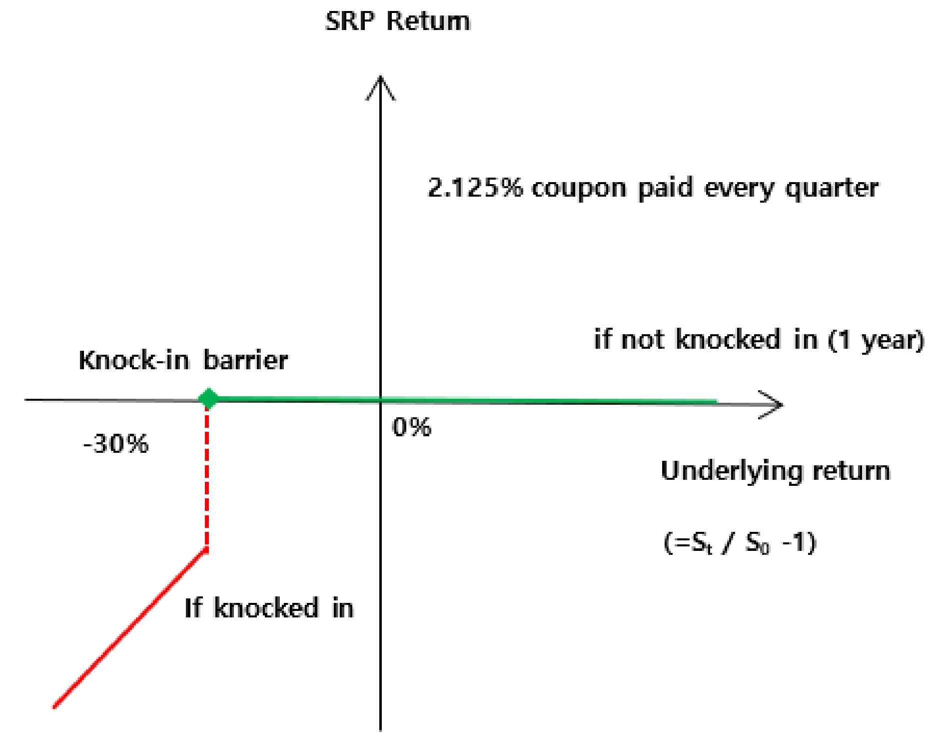
Panel A. Capital-protected participation product



Panel B. Non-capital-protected Participation product



Panel C. Reverse convertible



Panel D. Autocall

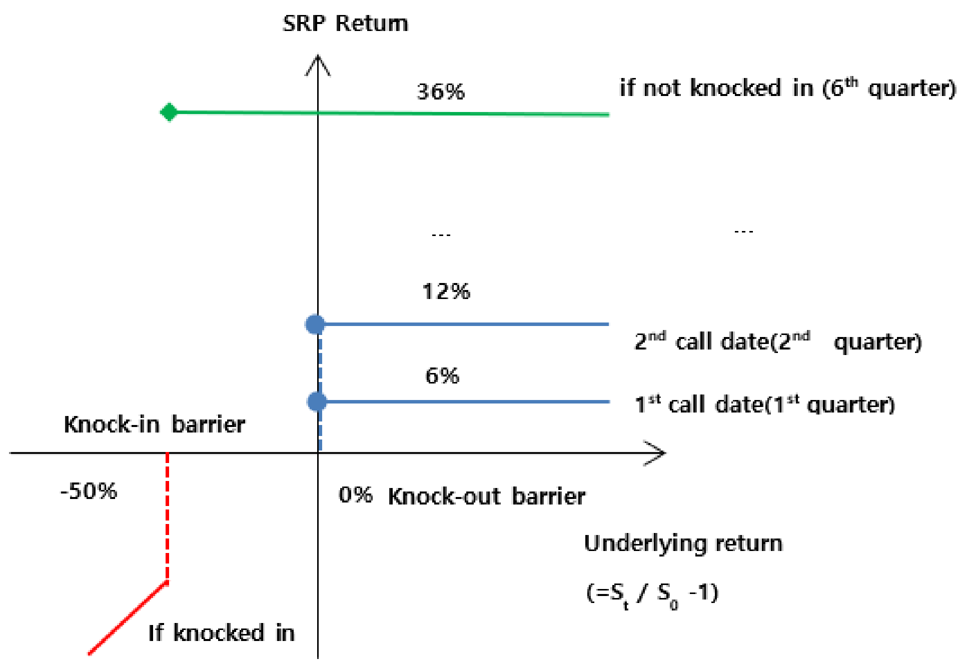


Figure 3: Categorization of SRPs
In this figure I present the categorization of SRPs according to the main features of their payoff structures, as described in Section 3.2.

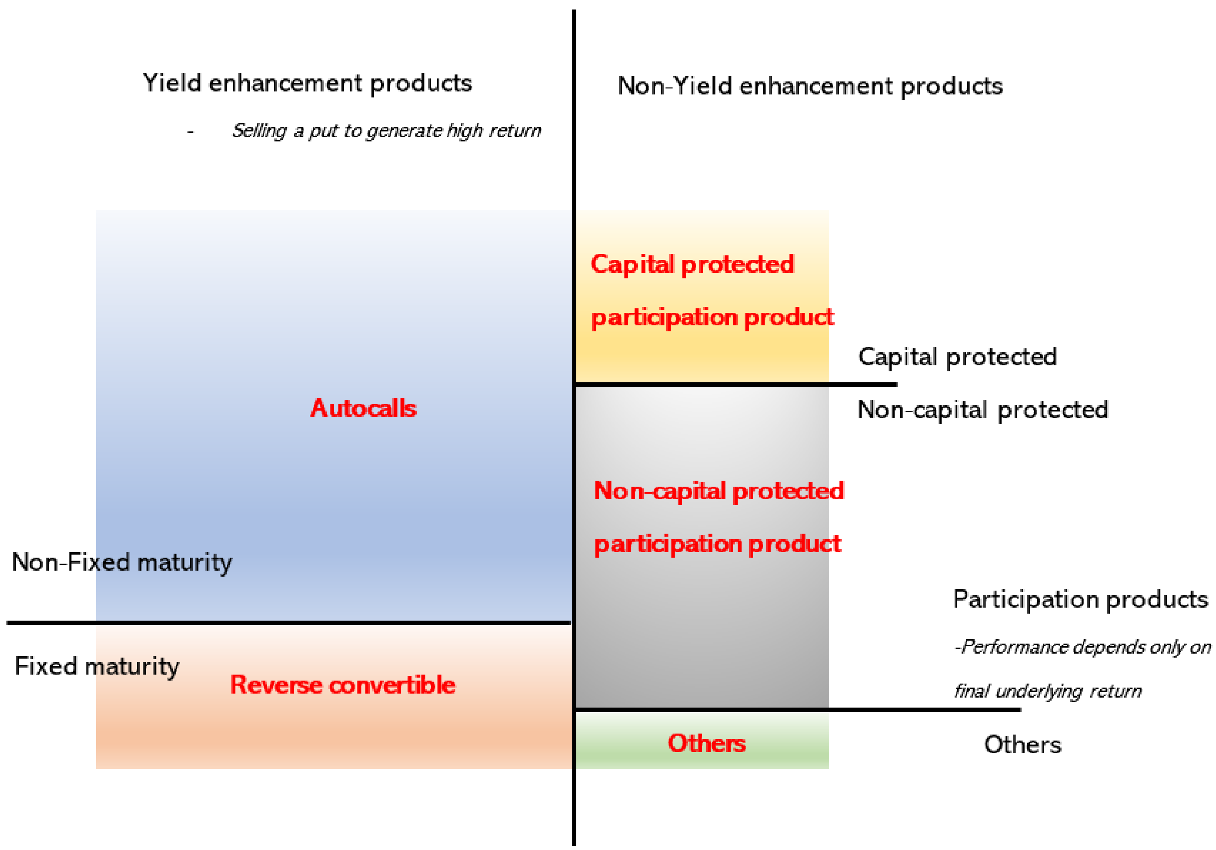


Figure 4: Validity of text mining techniques
In this figure I compare the annualized realized returns provided by the data provider and the annualized realized returns calculated based on the text mining technique described in Section 4.1. The sample size for this figure is 7,411 and the correlation coefficient between these two variables is 0.97.

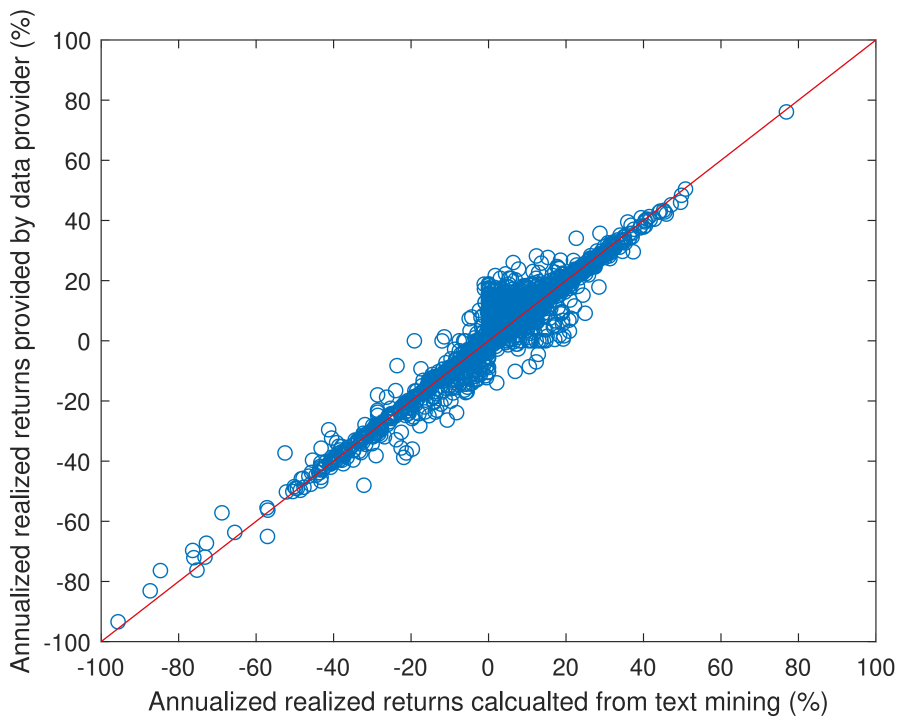


Figure 5: Distribution of ex-post performance of SRPs
This figure plots histograms of annualized realized returns across various types of SRPs: capita-protected participation products, non-capital-protected participation products, reverse convertibles, autocalls, and others. Annualized realized returns are calculated based on the text mining technique described in Section 4.1. The units along the x axis (y axis) are percentages (frequency).

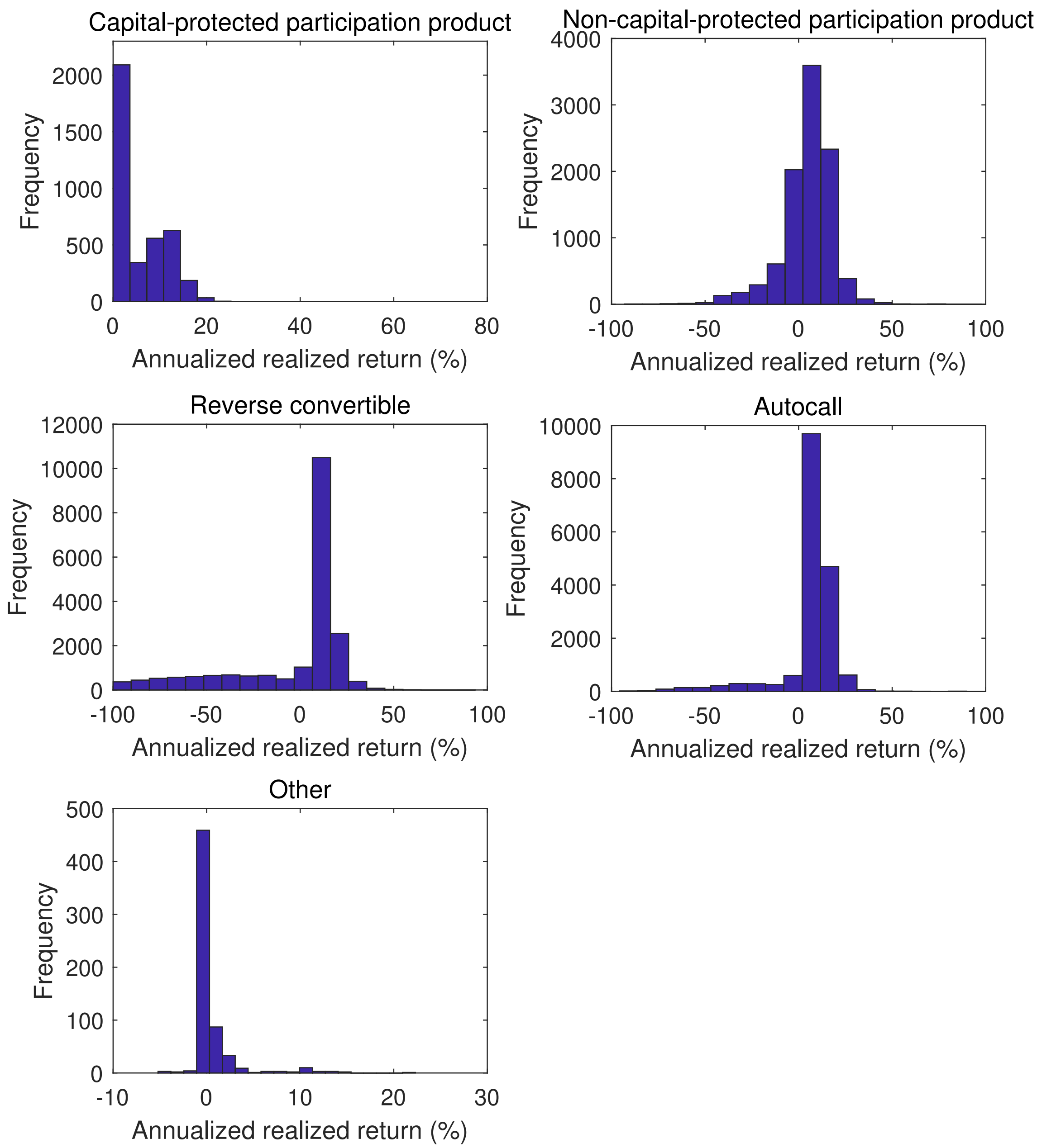


Figure 6: Comparison between estimated markup and reported markup

In this figure I compare the annualized markups estimated with the stochastic volatility model (Heston, 1993) and annualized markups based on the fair values of SRPs reported by issuers. The sample for this figure is based on short and medium term (term $<$ 5 years) S&P 500-linked SRPs issued in the United States during 2013 - 2016. The red line is a fitted line estimated from the least square method. The size of the sample is 3,563 and the correlation coefficient between the two variables is 0.72.

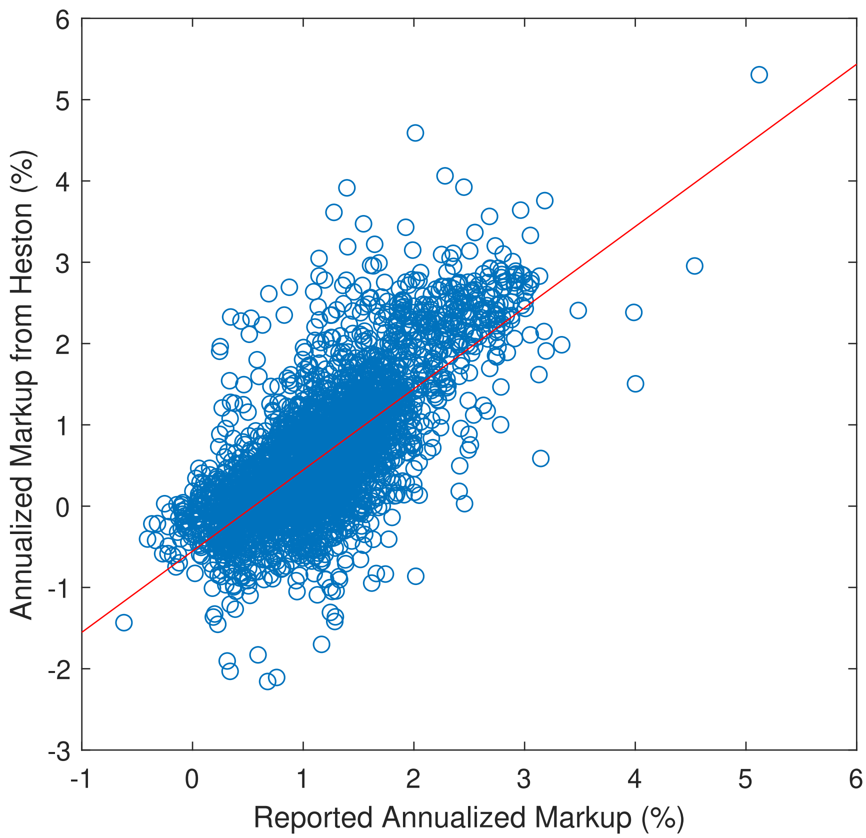


Figure 7: Evoluation of annualized markup of S&P 500-linked SRPs
In this figure I trace the evolution of annualized markup over the sample period of 2004 - 2016. This figure is constructed based on all SRPs that have the S&P 500 as underlying asset with terms of less than five years. The sample size for this figure is 7,117. The blue bars are the medians of annualized markups for all SRPs issued in each year. The red line plots the number of issuers that issue S&P 500-linked SRPs in each year.

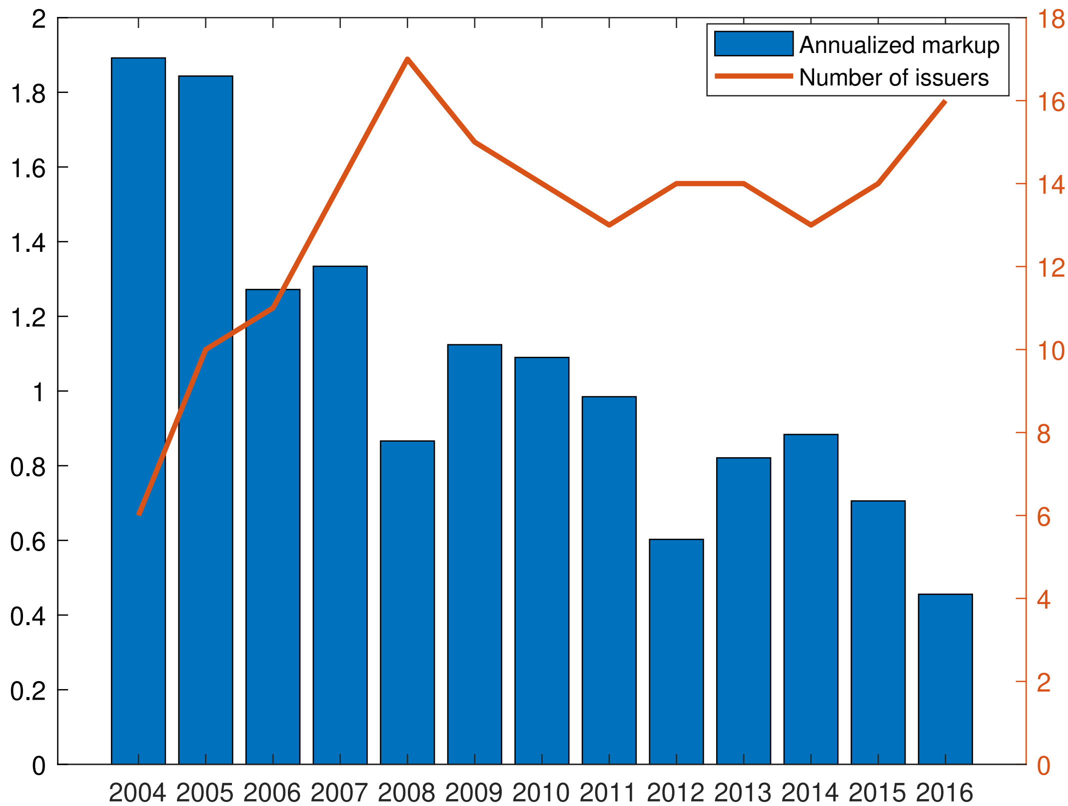


Table 1: An example of data structure
In this table I present the format of a product description in the SRP database. The example product, *Autocallable Optimization Securities with Contingent Protection*, is described in detail in Section 2.3.

<table>
<tr><th>Term</th><th>Detail</th></tr>
<tr><td>Product name</td><td>Autocallable Optimization Securities with Contingent Protection</td></tr>
<tr><td>ISIN code</td><td>US40428H5990</td></tr>
<tr><td>CUSIP</td><td>40428H599</td></tr>
<tr><td>Date of issuance</td><td>26 Mar 2008</td></tr>
<tr><td>Date of final valuation</td><td>25 Sep 2009</td></tr>
<tr><td>Date of maturity</td><td>30 Sep 2009</td></tr>
<tr><td>Underlying asset</td><td>S&P 500</td></tr>
<tr><td>Distributor</td><td>UBS</td></tr>
<tr><td>Issuer</td><td>HSBC Bank</td></tr>
<tr><td>Sales volume</td><td>$16.40 million</td></tr>
<tr><td>Sales commmission</td><td>1.5%</td></tr>
<tr><td>Early redemption information</td><td>
<table>
<tr><th>Knockout Date</th><th>Knockout Level</th><th>Payout</th></tr>
<tr><td>25 Jun 2008</td><td>0%</td><td>106.00%</td></tr>
<tr><td>25 Sep 2008</td><td>0%</td><td>112.00%</td></tr>
<tr><td>25 Dec 2008</td><td>0%</td><td>118.00%</td></tr>
<tr><td>26 Mar 2009</td><td>0%</td><td>124.00%</td></tr>
<tr><td>25 Jun 2009</td><td>0%</td><td>130.00%</td></tr>
<tr><td>25 Sep 2009</td><td>0%</td><td>136.00%</td></tr>
</table>
</td></tr>
<tr><td>Payoff description</td><td>This is a growth product linked to the S&P500.

The product terminates early if the index level at the end of each quarter is equal to or greater than the initial index level. In this case, the capital return is calculated using an annualized return of 24%. Otherwise, the product is held till maturity.

At maturity, if the index level never closed below 50% of the initial level, the product offers a capital return of 100%. If, however, the index closed below 50% of the initial index level on any trading day during the observation period, the capital return is 100% minus 1% for every 1% fall in the index over the investment period.</td></tr>
</table>

Table 2: Summary statistics

In this table I present product-level and group-level summary statistics on product characteristics of SRPs issued in the United States during the sample period of 2001 - 2016. In Panel A (Panel B) I describe product-level (group -level) summary statistics. The construction of group-level data using product-level data is summarized in Section 4.4. *Complexity (Autocall)* is a dummy equal to 1 if a product has the autocallable feature and 0 otherwise. *Complexity (# of scenarios)* is the number of scenarios in each of which the payoff of *Complexity (# of characters)* is the number of characters that describe the payoff structure where the unit is 1,000 characters. *Sales volume* is dollar amount of sales at issuance. *Annualized realized return* is ex-post performance measure of an SRP defined in Section 4.2.2. *Annualized markup* is defined as $\frac{1}{\text{Time to Maturity}}\left(\frac{\text{Price of a SRP - Fair value of a SRP}}{\text{Price of a SRP}}\right)$, where the fair value of an SRP is estimated from the stochastic volatility model of Heston (1993). *Sales commission* is a fixed proportion of sales volume paid to brokers. *Term* is years between the issuance date and the specified maturity date. *One-year CDS spread* is the one-year CDS spread of an issuer of an SRP. *Volatility* is the volatility of an SRP.

Panel A. Summary statistics (Product-level)

Variables	Average	Std. dev.	25th Percentile	Median	75th Percentile	N
Complexity measures						
Complexity (Autocall)	0.25	0.43	0	0	0	71,300
Complexity (# of scenarios)	5.14	6.72	3	3	5	67,861
Complexity (# of characters)	0.59	0.23	0.41	0.58	0.71	71,300
Sales volume ($ million)	4.69	12.57	0.34	1.50	4.61	71,300
Annualized realized return (%)	1.97	22.97	0.77	9.31	12.82	51,606
Annualized markup (%)	2.53	4.14	0.38	1.36	3.26	29,273
Sales commission (%)	1.91	1.26	1.25	1.65	2.50	62,164
Term (years)	2.37	2.41	1.01	1.27	3.02	71,300
One-year CDS spread (%)	0.63	0.72	0.27	0.40	0.77	56,667
Volatility (%)	20.05	10.51	12.16	18.01	25.13	39,032

Panel B. Summary statistics (Group-level)

Variables	Average	Std. dev.	25th Percentile	Median	75th Percentile	N
Complexity measures						
Complexity (Autocall)	0.21	0.41	0	0	0	1,575
Complexity (# of scenarios)	4.27	3.81	3	3	4	1,561
Complexity (# of characters)	0.56	0.19	0.42	0.51	0.69	1,575
Past return (%)	4.57	15.7	0.18	8.50	12.1	1,575
Normalized sales (%)	20.4	19.4	0.04	15.4	27.7	1,575
Annualized realized return (%)	4.22	13.67	0.52	8.56	10.91	1,365
Annualized markup (%)	2.20	2.71	0.78	1.54	3.13	947
Sales commission (%)	1.89	0.81	1.51	1.76	2.04	1,473
Term (years)	2.18	1.78	1.02	1.52	3.01	1,575
One-year CDS spread (%)	0.64	0.60	0.29	0.41	0.82	1,554
Volatility (%)	19.60	8.13	13.96	18.15	23.20	769

Table 3: Ex-post performance of SRPs

In the following table, I summarize the annualized realized returns of equity-linked SRPs issued in the United States during the sample period of 2001 - 2016 that matured before January 1, 2017. In Panel A I report the unweighted and sales-volume-weighted average and standard deviation of annualized realized returns for capital-protected participation products, non-capital-protected participation products products, reverse convertibles, autocalls, and others. ***Proportion of gain*** is the number of products that provided positive returns as the percentage of total products. In Panel B I report the annualized realized returns for other benchmark asset classes during the same period.

Panel A. Annualized realized returns and proportion of gain of SRPs

	Annualized realized returns (%)				Proportion	
	Unweighted		Sales-volume -weighted		of gain (%)	*N*
	Average	Std. dev	Average	Std. dev		
Capital-protected participation product	5.00	6.03	3.30	5.19	69.98	3,847
Non-capital-protected participation product	5.05	13.69	4.00	16.32	69.03	9,716
Reverse convertible	-4.20	31.27	-2.84	29.03	71.11	20,250
Autocall	6.86	15.53	7.59	13.44	88.32	17,168
Others	0.75	2.43	0.77	2.34	25.28	625
Total	1.97	22.97	3.20	19.16	75.81	51,606

Panel B. Annualized realized returns of other benchmark asset classes

	Average	Std. dev
Bank (AAA) Bond Yield(1 year)	3.7	1.43
S&P 500	6.39	14.6

Panel C. Annualized realized returns of SRPs (sales-volume-weighted)

Year	Capital protected participation product	Non-capital protected participation product	Reverse convertible	Autocall	Others	Total
2006	N.A.	10.73	-5.55	14.45	N.A.	0.15
2007	8.49	8.54	8.30	10.99	N.A.	8.46
2008	0.80	-8.47	-19.77	1.41	1.65	-13.62
2009	0.18	-15.65	-16.92	16.46	0.31	-10.69
2010	0.94	10.60	8.08	10.91	0.19	8.55
2011	0.54	8.40	-1.54	10.09	0.69	4.07
2012	1.47	6.60	1.49	7.02	1.72	4.68
2013	4.55	12.70	8.46	8.70	2.50	9.95
2014	6.38	12.06	10.11	9.49	1.21	10.38
2015	5.77	8.59	1.32	5.49	1.72	6.76
2016	4.28	-0.85	1.09	3.28	1.48	0.69
Total (including products matured before 2006)	3.30	4.00	-2.84	7.59	0.77	3.20

Table 4: Extrapolation and sales

In the following table I report the effects of extrapolative expectations on SRP sales. In Panel A I report the coefficients of regressions in which dependent variables are *Normalized sales*). In Panel B I report the coefficients of regressions of *Normalized sales* on explanatory variables with control variables excluding ***Annualized markup*** and ***Volatility***. In Panel C I report the coefficients of regressions of *Normalized sales* on explanatory variables with control variables including ***Annualized markup*** and ***Volatility***. Explanatory variables and control variables in the tables are defined in Section 4.4. In each column of the regression tables, I report coefficients and their heteroscedasticity-robust standard errors in parentheses. Standard errors are clustered at the underlying asset group level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Normalized sales and past return

	Normalized sales							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Past return	0.264	0.204	0.168	0.102	-0.032	-0.065	-0.058	-0.130
	(0.043)	(0.042)	(0.035)	(0.039)	(0.092)	(0.087)	(0.127)	(0.100)
Complexity (Autocall)			0.132	0.134				
			(0.015)	(0.018)				
Complexity (Autocall)×Past return			0.443	0.367				
			(0.106)	(0.081)				
Complexity (# of scenarios)					0.003	0.005		
					(0.003)	(0.003)		
Complexity (# of scenarios)×Past return					0.071	0.062		
					(0.025)	(0.020)		
Complexity (# of characters)							0.299	0.303
							(0.039)	(0.043)
Complexity (# of characters)×Past return							0.564	0.549
							(0.209)	(0.157)
Quarter FE		X		X		X		X
Underlying FE		X		X		X		X
N	1,575	1,570	1,575	1,570	1,561	1,557	1,575	1,570
adj. R^2	0.052	0.196	0.196	0.320	0.085	0.230	0.174	0.299

Panel B. Normalized sales and past return with controls (without annualized markup and volatility)

	Normalized sales							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Past return	0.229	0.211	0.123	0.0961	-0.104	-0.094	-0.149	-0.173
	(0.0399)	(0.0377)	(0.028)	(0.034)	(0.078)	(0.081)	(0.106)	(0.0904)
Complexity (Autocall)			0.0958	0.116				
			(0.014)	(0.017)				
Complexity (Autocall)×Past return			0.484	0.392				
			(0.107)	(0.0774)				
Complexity (# of scenarios)					0.001	0.003		
					(0.003)	(0.003)		
Complexity (# of scenarios)×Past return					0.077	0.067		
					(0.022)	(0.019)		
Complexity (# of characters)							0.177	0.227
							(0.0488)	(0.0489)
Complexity (# of characters)×Past return							0.639	0.627
							(0.182)	(0.150)
Sales commission	0.721	-1.704	1.392	-0.778	0.477	-1.819	1.022	-1.182
	(0.984)	(1.145)	(0.725)	(1.105)	(1.013)	(1.226)	(0.842)	(1.096)
Term	-4.064	-2.629	-3.676	-2.479	-0.039	-0.024	-3.227	-1.855
	(0.348)	(0.609)	(0.334)	(0.558)	(0.004)	(0.006)	(0.356)	(0.634)
One-year CDS spread	-4.346	-1.403	-4.436	-2.113	-5.148	-2.398	-4.526	-1.548
	(1.146)	(1.756)	(1.137)	(1.857)	(1.173)	(2.026)	(1.185)	(2.070)
Quarter FE		X		X		X		X
Underlying FE		X		X		X		X
N	1,468	1,460	1,468	1,460	1,464	1,457	1,468	1,460
adj. R^2	0.188	0.255	0.289	0.361	0.212	0.280	0.235	0.317

Panel C. Normalized sales and past return with controls (with annualized markup and volatility)

	Normalized sales							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Past return	0.214	0.181	0.073	0.053	-0.218	-0.226	-0.393	-0.413
	(0.055)	(0.049)	(0.039)	(0.049)	(0.089)	(0.075)	(0.134)	(0.157)
Complexity (Autocall)			0.126	0.148				
			(0.014)	(0.015)				
Complexity (Autocall)×Past return			0.510	0.388				
			(0.132)	(0.101)				
Complexity (# of scenarios)					0.020	0.027		
					(0.004)	(0.003)		
Complexity (# of scenarios)×Past return					0.100	0.086		
					(0.020)	(0.016)		
Complexity (# of characters)							0.316	0.338
							(0.053)	(0.040)
Complexity (# of characters)×Past return							0.974	0.921
							(0.240)	(0.260)
Sales commission	-1.247	-5.947	3.302	-0.672	0.885	-3.711	2.411	-1.025
	(3.029)	(2.656)	(2.296)	(2.364)	(3.365)	(3.358)	(2.649)	(2.541)
Term	-5.043	-2.808	-4.570	-2.881	-0.041	-0.016	-3.528	-1.931
	(0.911)	(1.299)	(0.687)	(0.870)	(0.010)	(0.013)	(0.636)	(0.835)
One-year CDS spread	-4.305	-6.000	-5.022	-5.271	-4.809	-4.786	-4.722	-4.927
	(1.531)	(2.923)	(1.486)	(2.780)	(1.456)	(2.734)	(1.618)	(2.685)
Annualized markup	-1.023	-1.077	-0.582	-0.656	-0.769	-0.859	-0.920	-0.938
	(0.304)	(0.331)	(0.331)	(0.356)	(0.220)	(0.242)	(0.298)	(0.326)
Volatility	0.201	-0.380	0.428	0.136	0.417	0.069	0.310	-0.120
	(0.153)	(0.223)	(0.138)	(0.205)	(0.151)	(0.168)	(0.140)	(0.156)
Quarter FE		X		X		X		X
Underlying FE		X		X		X		X
N	746	739	746	739	746	739	746	739
adj. R^2	0.159	0.247	0.302	0.386	0.258	0.357	0.267	0.359

Table 5: Extrapolation and sales (Issuer level)
In the following table I repeat the analysis of Table 4 with issuer level data. In Panel A I report the coefficients of regressions in which dependent variables are *Normalized sales*). In Panel B I report the coefficients of regressions of *Normalized sales* on explanatory variables with control variables excluding *Annualized markup* and *Volatility*. In Panel C I report the coefficients of regressions of *Normalized sales* on explanatory variables with control variables including *Annualized markup* and *Volatility*. Explanatory variables and control variables in the tables are defined in Section 4.4. In each column of the regression tables, I report coefficients and their heteroscedasticity-robust standard errors in parentheses. Standard errors are clustered at the underlying asset group level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Normalized sales and past return

	Normalized sales							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Past return	0.299	0.297	0.207	0.210	0.108	0.118	-0.0953	-0.205
	(0.057)	(0.036)	(0.047)	(0.044)	(0.045)	(0.053)	(0.068)	(0.117)
Complexity (Autocall)			0.154	0.119				
			(0.023)	(0.018)				
Complexity (Autocall)×Past return			0.409	0.328				
			(0.056)	(0.063)				
Complexity (# of scenarios)					0.007	0.004		
					(0.003)	(0.001)		
Complexity (# of scenarios)×Past return					0.043	0.039		
					(0.011)	(0.008)		
Complexity (# of characters)							0.423	0.244
							(0.027)	(0.029)
Complexity (# of characters)×Past return							0.663	0.785
							(0.145)	(0.168)
Quarter FE		X		X		X		X
Underlying FE		X		X		X		X
Issuer FE		X		X		X		X
N	5,764	5,752	5,764	5,752	5,703	5,691	5,764	5,752
adj. R^2	0.025	0.215	0.103	0.249	0.053	0.226	0.149	0.246

Panel B. Normalized sales and past return with controls (without annualized markup and volatility)

	Normalized sales							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Past return	0.287	0.268	0.195	0.140	0.113	0.104	-0.128	-0.202
	(0.075)	(0.050)	(0.060)	(0.061)	(0.041)	(0.080)	(0.087)	(0.174)
Complexity (Autocall)			0.133	0.136				
			(0.013)	(0.018)				
Complexity (Autocall)×Past return			0.429	0.349				
			(0.076)	(0.089)				
Complexity (# of scenarios)					0.008	0.006		
					(0.001)	(0.001)		
Complexity (# of scenarios)×Past return					0.038	0.032		
					(0.015)	(0.014)		
Complexity (# of characters)							0.299	0.254
							(0.024)	(0.024)
Complexity (# of characters)×Past return							0.707	0.716
							(0.194)	(0.248)
Sales commission	3.013	-0.518	3.088	0.450	3.196	-0.160	2.555	-0.0221
	(0.794)	(0.729)	(0.596)	(0.697)	(0.701)	(0.709)	(0.654)	(0.719)
Term	-0.052	-0.0125	-0.046	-0.018	-0.055	-0.020	-0.040	-0.015
	(0.004)	(0.007)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)
One-year CDS spread	-2.512	-0.714	-1.046	-0.743	-2.074	-0.418	-1.343	-0.465
	(1.043)	(0.946)	(0.901)	(1.114)	(1.019)	(1.000)	(0.957)	(0.991)
Quarter FE		X		X		X		X
Underlying FE		X		X		X		X
Issuer FE		X		X		X		X
N	3,385	3,382	3,385	3,382	3,372	3,370	3,385	3,382
adj. R^2	0.094	0.174	0.167	0.223	0.126	0.190	0.156	0.210

Panel C. Normalized sales and past return with controls (with annualized markup and volatility)

	Normalized sales							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Past return	0.273	0.305	0.153	0.152	0.042	0.139	-0.419	-0.277
	(0.095)	(0.064)	(0.081)	(0.063)	(0.066)	(0.060)	(0.135)	(0.141)
Complexity (Autocall)			0.149	0.147				
			(0.014)	(0.024)				
Complexity (Autocall)×Past return			0.441	0.321				
			(0.091)	(0.104)				
Complexity (# of scenarios)					0.009	0.005		
					(0.001)	(0.001)		
Complexity (# of scenarios)×Past return					0.048	0.030		
					(0.013)	(0.009)		
Complexity (# of characters)							0.327	0.274
							(0.027)	(0.031)
Complexity (# of characters)×Past return							1.076	0.812
							(0.215)	(0.204)
Sales commission	2.720	-1.130	3.352	0.580	2.827	-0.722	2.299	-0.195
	(1.417)	(1.466)	(0.957)	(1.370)	(1.365)	(1.459)	(1.175)	(1.467)
Term	-0.058	-0.013	-0.047	-0.014	-0.068	-0.024	-0.046	-0.020
	(0.011)	(0.016)	(0.007)	(0.013)	(0.009)	(0.012)	(0.008)	(0.012)
One-year CDS spread	-3.931	0.314	-2.309	0.846	-3.596	0.797	-2.799	0.969
	(1.492)	(1.406)	(1.421)	(1.838)	(1.502)	(1.457)	(1.470)	(1.564)
Annualized markup	-0.421	-0.919	-0.00161	-0.392	-0.497	-0.883	-0.465	-0.697
	(0.436)	(0.371)	(0.327)	(0.342)	(0.478)	(0.372)	(0.387)	(0.347)
Volatility	0.011	-0.105	0.370	0.227	0.195	0.0245	0.254	0.040
	(0.123)	(0.112)	(0.090)	(0.096)	(0.095)	(0.130)	(0.109)	(0.105)
Quarter FE		X		X		X		X
Underlying FE		X		X		X		X
Issuer FE		X		X		X		X
N	1,882	1,881	1,882	1,881	1,882	1,881	1,882	1,881
adj. R^2	0.069	0.166	0.146	0.208	0.103	0.174	0.141	0.197

Table 6: Effect of rational expectation

In this table I report the effects of rational expectation on the sales dynamics of the SRP market. *Annualized realized return of newly issued products* measures annualized realized returns of newly issued products, which are realized later depending on the lengths of terms. Explanatory variables, *Past return* and *Normalized sales*, are defined in Section 4.4. I round *Term* and use it for fixed effect to control different terms of SRPs. In each column, I report coefficients and their heteroscedasticity-robust standard errors in parentheses. Standard errors are clustered at the underlying asset group level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Annualized realized return of newly issued products			
	(1)	(2)	(3)	(4)
Past return	-0.031	-0.031		
	(0.024)	(0.037)		
Normalized sales			0.025	0.036
			(0.023)	(0.022)
Quarter FE		X		X
Underlying FE		X		X
Term FE		X		X
N	1,365	1,365	1,365	1,365
adj. R^2	0.001	0.301	0.000	0.303

Table 7: Extrapolation and salient thinking
In this table I report the effects of extrapolative expectations and salient thinking on SRP sales. I restrict the sample to reverse convertibles and autocalls because other products do not have headline rates by their designs. Explanatory variables and *Normalized sales* are defined in Section 4.4. In each column, I report coefficients and their heteroscedasticity-robust standard errors in parentheses. Standard errors are clustered at the underlying asset group level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Extrapolation and salient thinking

	Normalized sales					
	(1)	(2)	(3)	(4)	(5)	(6)
Past return	0.383	0.231	0.312	0.228	0.276	0.239
	(0.047)	(0.062)	(0.047)	(0.062)	(0.043)	(0.060)
Headline rate	1.958	2.594	2.303	2.617	2.628	2.719
	(0.335)	(0.519)	(0.385)	(0.573)	(0.464)	(0.592)
Sales commission			-0.957	-1.064	-3.841	-1.855
			(1.696)	(2.401)	(3.674)	(5.248)
Term			-0.010	0.033	-0.003	0.050
			(0.010)	(0.020)	(0.015)	(0.016)
One-year CDS spread			-7.213	-5.310	-7.914	-5.413
			(1.627)	(5.475)	(1.542)	(9.162)
Annualized markup					-0.846	-0.629
					(0.245)	(0.418)
Volatility					0.0660	-0.778
					(0.162)	(0.289)
Quarter FE		X		X		X
Underlying FE		X		X		X
N	794	793	783	782	570	570
adj. R^2	0.143	0.265	0.168	0.273	0.194	0.324

Panel B. Headline rate and complexity

	Headline rate	
	(1)	(2)
Complexity (Autocall)	0.006	0.018
	(0.003)	(0.002)
Quarter FE		X
Underlying FE		X
N	794	793
adj. R^2	0.009	0.628

Table 8: Effect of extrapolation on markup and sales commission
In this table I report the effects of investor extrapolation on changes in annualized markups and sales commissions based on annual frequency data. In Panel A (Panel B) I show the coefficients of regressions in which the dependent variable is Δ*Annualized markup* (Δ*Sales commission*). Δ*Annualized markup* is the changes in median annualized markups between current and previous period and Δ*Sales commission* is the changes in median sales commissions between current and previous periods described in Section . The explanatory variables are defined in Section 4.4. In each column, I report coefficients and their heteroscedasticity-robust standard errors in parentheses. Standard errors are clustered at the underlying asset level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Change of annualized markup and past return

	ΔAnnualized markup			
Sample	Unweighted		Sales-volume-weighted	
	(1)	(2)	(3)	(4)
Past return	-0.041	-0.075	-0.019	-0.051
	(0.023)	(0.021)	(0.0060)	(0.008)
Complexity (Autocall)		-0.761		-0.547
		(0.310)		(0.234)
Complexity (Autocall)× Past return		0.077		0.060
		(0.021)		(0.007)
Past outstanding		-0.026		-0.010
		(0.015)		(0.008)
Past outstanding × Past return		0.004		0.002
		(0.001)		(0.0005)
Year FE×Underlying FE	X	X	X	X
Term FE	X	X	X	X
N	717	717	717	717
adj. R^2	0.254	0.257	0.215	0.217

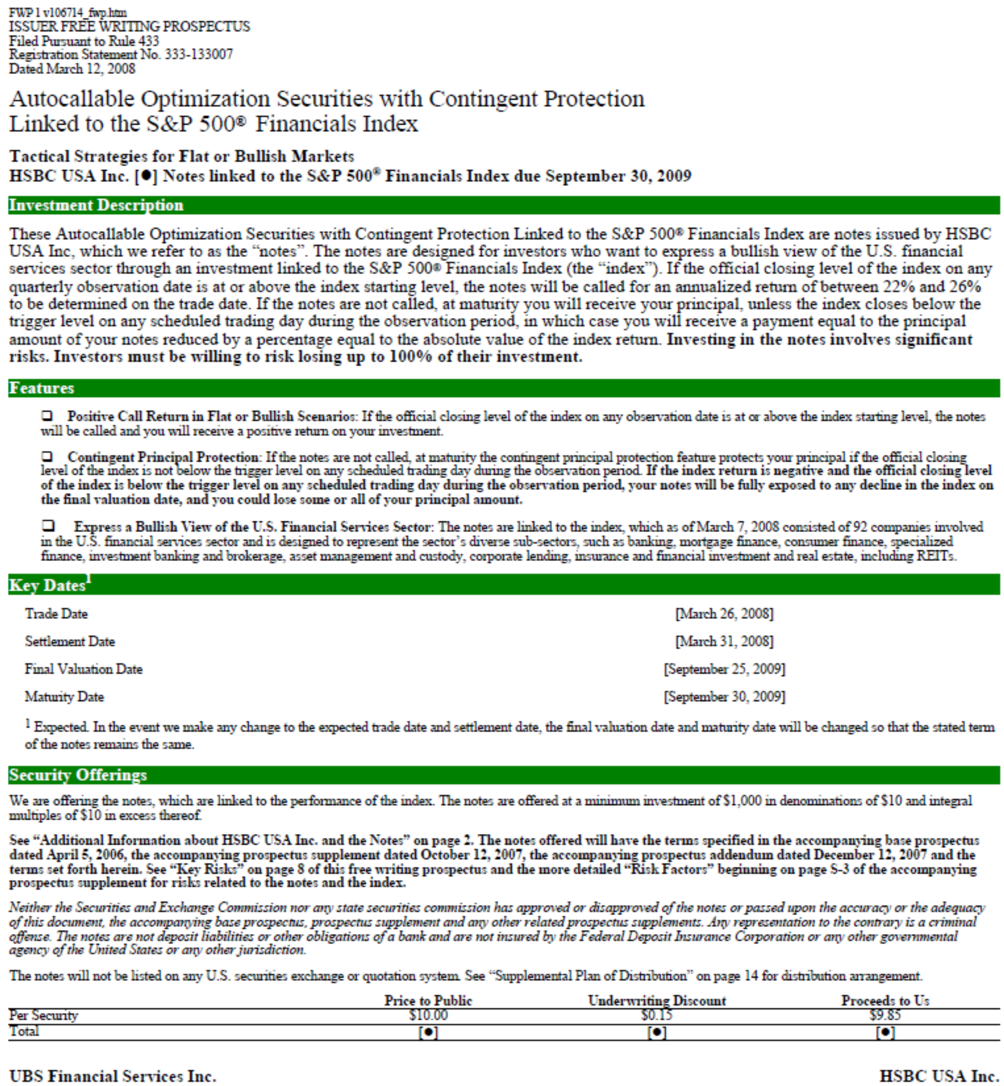
Panel B. Change of sales commission and past return

	ΔSales commission			
Sample	Unweighted		Sales-volume-weighted	
	(1)	(2)	(3)	(4)
Past return	-0.004	0.003	-0.001	0.008
	(0.007)	(0.010)	(0.007)	(0.012)
Complexity (Autocall)		0.067		0.068
		(0.051)		(0.045)
Complexity (Autocall)× Past return		-0.013		-0.015
		(0.006)		(0.006)
Past outstanding		0.015		0.014
		(0.003)		(0.003)
Past outstanding × Past return		-0.001		-0.001
		(0.0006)		(0.001)
Year FE×Underlying FE	X	X	X	X
Term FE	X	X	X	X
N	1,564	1,564	1,564	1,564
adj. R^2	0.081	0.086	0.035	0.042

Appendix

Appendix A: An example of prospectus

This figure is the first two pages of prospectus for *Autocallable Optimization Securities with Contingent Protection*. The detailed description of this product is provided in Section 2.2.



FWP 1 v106714_fwp.htm
ISSUER FREE WRITING PROSPECTUS
Filed Pursuant to Rule 433
Registration Statement No. 333-133007
Dated March 12, 2008

Autocallable Optimization Securities with Contingent Protection
Linked to the S&P 500® Financials Index

Tactical Strategies for Flat or Bullish Markets
HSBC USA Inc. [●] Notes linked to the S&P 500® Financials Index due September 30, 2009

Investment Description

These Autocallable Optimization Securities with Contingent Protection Linked to the S&P 500® Financials Index are notes issued by HSBC USA Inc, which we refer to as the "notes". The notes are designed for investors who want to express a bullish view of the U.S. financial services sector through an investment linked to the S&P 500® Financials Index (the "index"). If the official closing level of the index on any quarterly observation date is at or above the index starting level, the notes will be called for an annualized return of between 22% and 26% to be determined on the trade date. If the notes are not called, at maturity you will receive your principal, unless the index closes below the trigger level on any scheduled trading day during the observation period, in which case you will receive a payment equal to the principal amount of your notes reduced by a percentage equal to the absolute value of the index return. **Investing in the notes involves significant risks. Investors must be willing to risk losing up to 100% of their investment.**

Features

- ❑ **Positive Call Return in Flat or Bullish Scenarios**: If the official closing level of the index on any observation date is at or above the index starting level, the notes will be called and you will receive a positive return on your investment.
- ❑ **Contingent Principal Protection**: If the notes are not called, at maturity the contingent principal protection feature protects your principal if the official closing level of the index is not below the trigger level on any scheduled trading day during the observation period. **If the index return is negative and the official closing level of the index is below the trigger level on any scheduled trading day during the observation period, your notes will be fully exposed to any decline in the index on the final valuation date, and you could lose some or all of your principal amount.**
- ❑ **Express a Bullish View of the U.S. Financial Services Sector**: The notes are linked to the index, which as of March 7, 2008 consisted of 92 companies involved in the U.S. financial services sector and is designed to represent the sector's diverse sub-sectors, such as banking, mortgage finance, consumer finance, specialized finance, investment banking and brokerage, asset management and custody, corporate lending, insurance and financial investment and real estate, including REITs.

Key Dates[1]

Trade Date	[March 26, 2008]
Settlement Date	[March 31, 2008]
Final Valuation Date	[September 25, 2009]
Maturity Date	[September 30, 2009]

[1] Expected. In the event we make any change to the expected trade date and settlement date, the final valuation date and maturity date will be changed so that the stated term of the notes remains the same.

Security Offerings

We are offering the notes, which are linked to the performance of the index. The notes are offered at a minimum investment of $1,000 in denominations of $10 and integral multiples of $10 in excess thereof.

See "Additional Information about HSBC USA Inc. and the Notes" on page 2. The notes offered will have the terms specified in the accompanying base prospectus dated April 5, 2006, the accompanying prospectus supplement dated October 12, 2007, the accompanying prospectus addendum dated December 12, 2007 and the terms set forth herein. See "Key Risks" on page 8 of this free writing prospectus and the more detailed "Risk Factors" beginning on page S-3 of the accompanying prospectus supplement for risks related to the notes and the index.

Neither the Securities and Exchange Commission nor any state securities commission has approved or disapproved of the notes or passed upon the accuracy or the adequacy of this document, the accompanying base prospectus, prospectus supplement and any other related prospectus supplements. Any representation to the contrary is a criminal offense. The notes are not deposit liabilities or other obligations of a bank and are not insured by the Federal Deposit Insurance Corporation or any other governmental agency of the United States or any other jurisdiction.

The notes will not be listed on any U.S. securities exchange or quotation system. See "Supplemental Plan of Distribution" on page 14 for distribution arrangement.

	Price to Public	Underwriting Discount	Proceeds to Us
Per Security	$10.00	$0.15	$9.85
Total	[●]	[●]	[●]

UBS Financial Services Inc. **HSBC USA Inc.**

Indicative Terms

Issuer	HSBC USA Inc. (Aa3/AA-)[1]
Principal Amount	$10 per note
Term	18 months, unless earlier called
Index	The S&P 500® Financials Index (Ticker: S5FINL) (the "index")
Call Feature	The notes will be called if the official closing level of the index on any observation date is at or above the index starting level
Observation Dates	On or about June 26, 2008, September 26, 2008, December 26, 2008, March 26, 2009, June 26, 2009 and September 25, 2009
Call Settlement Dates	Three business days following the applicable observation date
Return on Call Date	If the notes are called, on a call settlement date, investors will receive a cash payment per $10 principal amount note equal to the call price for the applicable observation date. The return on call date will be based upon an annualized return of between 22% and 26%. The table below assumes an annualized return of 24% (the midpoint of 22% and 26%). The actual annualized return upon which the return on call date is based will be determined on the trade date
Observation Date	Return on Call Date Call Price (per $10.00)
June 25, 2008	[6.00]% $[10.60]
September 25, 2008	[12.00]% $[11.20]
December 26, 2008	[18.00]% $[11.80]
March 26, 2009	[24.00]% $[12.40]
June 25, 2009	[30.00]% $[13.00]
Final Valuation Date (September 25, 2009)	[36.00]% $[13.60]
Payment at Maturity (per $10 note)	**If the notes are not called and the official closing level of the index is not below the trigger level on any scheduled trading day during the observation period**, you will receive a cash payment on the maturity date equal to $10 per $10 principal amount note. **If the notes are not called and the official closing level of the index is below the trigger level on any scheduled trading day during the observation period**, you will receive a cash payment on the maturity date equal to: $\$10 \times (1 + \text{index return});$ **In this case, you may lose all or a substantial portion of your principal, depending on how much the index declines**
Index Return	$\frac{\text{index ending level - index starting level}}{\text{index starting level}}$
Trigger Level	[●], representing 50% of the index starting level
Observation Period	The period from, but excluding, the trade date to, and including, the final valuation date
Index Starting Level	The official closing level of the index on the trade date
Index Ending Level	The official closing level of the index on the final valuation date
Official Closing Level	The official closing level on any scheduled trading day during the observation period will be the closing level of the index as determined by the calculation agent based upon determinations with respect thereto made by the reference sponsor and displayed on Bloomberg Professional® service page "S5FINL<INDEX>".
CUSIP / ISIN	40428H 599 / US40428H5990

Determining Payment at Maturity

Appendix B: Text mining for payoff structure

In order to analyze the payoff structures of SRPs, I take a simple and precise text mining technique to fully interpret the payoff structures via the following steps.

First, I decompose the payoff descriptions into three parts: *coupon description*, *early termination description*, and *maturity payo description*. Then, for each part, I group the products whose descriptions have the same structure. I explain the basic idea of my text mining approach using the following hypothetical example for the maturity payoff description.

> ***Payoff description of product 1***: *At maturity, the product o ers a capital return of 100%, plus 300% of the rise in the index over the investment period, subject to a maximum overall return of 114%. If the nal index level is lower than its initial level, the capital return is 100% minus 1% for every 1% fall.*

> ***Payoff description of product 2***: *At maturity, the product provides a capital return of 100%, plus 200% of the rise in the underlying asset over the period of the investment, subject to the maximum cap of 124%. If the nal underlying asset is lower than its initial value, the capital return is 100% minus 1% for every 1% fall.*

The two paragraphs above describe the maturity payoff descriptions of two products. However, these seemingly different descriptions actually have the same structure. The main differences are in the expressions that each description employs. For example, the word *o ers* in the first paragraph has the same meaning as the word *provides* in the second paragraph. Likewise, the following pairs of words have the same meanings: *(o ers, provides), (index, underlying asset), (maximum overall return, maximum cap), (a, the), (initial value, initial level)*. By analyzing random samples of product descriptions, I construct a comprehensive dictionary that groups expressions that have similar meanings or communicate the same idea. Finally, I replace expressions that have similar meanings with a single expression. For example, I map *o ers* and *provides* into *o ers*. Through this approach, I form a manageable number of groups of product descriptions. By analyzing these groups of product descriptions, I fully interpret almost the entire sample of products. Of the 71,300 entire sample of products, I fully interpret 67,861 product descriptions. The remaining 3,439 product descriptions were incomplete and could not be analyzed.

Appendix C: Stochastic volatility model (Heston, 1993)

Under the risk neutral measure, the price (S_t) and variance (V_t) have the following dynamics.

$$\frac{dS_t}{S_t} = (r_f - q)dt + \sqrt{V_t}dW_t^1$$
$$dV_t = a(\bar{V} - V_t)dt + \eta\sqrt{V_t}dW_t^2$$
$$dW_t^1 dW_t^2 = \rho dt$$

Under the above assumptions, Heston (1993) derives the closed-form solutions of the call option price, $C_0^{Heston}(K,T)$:

$$C_0^{Heston}(K,T) = S_0\Pi_1 - e^{-(r_f - q)T}K\Pi_2$$
$$\text{where } \Pi_1 = \frac{1}{2} + \frac{1}{\pi}\int_0^\infty Re\left[\frac{e^{-iw\log(K)}\psi_{log(S_T)}(w-i)}{iw\psi_{\log(S_T)}(-i)}\right]dw$$
$$\Pi_2 = \frac{1}{2} + \frac{1}{\pi}\int_0^\infty Re\left[\frac{e^{-iw\log(K)}\psi_{log(S_T)}(w)}{iw}\right]dw$$

where K is the strike price of the call option, $\psi_{\log(S_t)}(w)$ is the characteristic function of $\log(S_t)$, and the function Re returns a real part of a complex number. A closed-from of the characteristics function, $\psi_{\log(S_t)}(w)$, is expressed as follows:

$$\psi_{\log(S_t)}(w) = e^{C(t,w)\bar{V} + D(t,w)V_0 + iw\log(S_0 e^{(r-q)T})}$$
$$where\ C(t,w) = a\left[r_- t - \frac{2}{\eta^2}\log\left(\frac{1-ge^{-ht}}{1-g}\right)\right]$$
$$D(t,w) = r_-\frac{1-e^{-ht}}{1-ge^{-ht}}$$
$$r_\pm = \frac{\beta \pm h}{\eta^2}; h = \sqrt{\beta^2 - 4\alpha\gamma}; g = \frac{r_-}{r_+}$$
$$\alpha = -\frac{w^2}{2} - \frac{iw}{2}; \beta = a - \rho\eta w i; \gamma = \frac{\eta^2}{2}$$

Appendix D: Survey on SRP investors' characteristics

In this table I display results of a survey on the characteristics of SRP investors conducted by the Financial Supervisory Service (FSS), a finance watchdog in South Korea, in August 2010. The FSS selected random sample of investors who visited one of 17 major SRP brokerage firms in South Korea. The total number of respondents is 1,049.

1. Gender

Male	Female
45.9%	54.1%

2. Age

20 - 29	30 - 39	40 - 49	50 - 59	Older than 60
18.1%	32.7%	23.2%	17.4%	8.6%

3. Occupation

Self Employed	Employee	Finance	Public sector	Others
11.6%	32.5%	29.2%	3%	23.8%

4. Education background

Elementary school	Middle school	High school	College	Graduate school
0.2%	1%	17.4%	75.2%	6.2%

5. Assets ($)

Less than 50k	50k - 100k	100k - 500k	500k - 1m	More than 1m
21.6%	12.9%	35.8%	16.5%	13.3%

6. Financial assets ($)

Less than 50k	50k - 100k	100k - 500k	500k - 1m	More than 1m
32.3%	26.2%	28.5%	8.0%	5.0%

7. Investment experience in SRPs

None	Less than 1 year	1-3 years	3-5 years	More than 5 years
20.0%	14.1%	44.2%	16.1%	5.6%

8. Amount of current investment in SRPs ($)

Less than 10k	10k - 50k	50k - 100k	100k - 500k	More than 500k
36.5%	35.8%	13.6%	11.7%	2.4%

9. Annualized realized returns in SPRs over the last 2 years

Less than -30%	-30 ~ -15%	-15% ~ -0%	0% ~ 10%	More than 10%
7%	6.6%	8.9%	39.1%	38.4%

10. What is your risk preference?

Extremely risk averse	Risk averse	Risk neutral	Risk seeking	Extremely risk seeking
1.3%	14%	18.1%	37.6%	29.1%

11. Investment experience in the last 6 months

Stock	Bond	Option Futures	Deposit	SRP
76.5%	34.8%	5.7%	59.7%	65.6%

12. (Subjective) Expected return on SRPs

Less than 4%	4~6%	6~9%	9~12%	More than 12%
0.9%	1.8%	13.7%	37.7%	45.9%

13. How did you start your first investment in SRPs?

Media	Brochures	Brokers	Friends	Internet
11.8%	14.5%	57.2%	9.3%	7.2%

14. Why do you invest in SRPs? (Multiple answers are possible.)

Reputation of issuers	Safe underlying	High expected returns	Principal is protected	Others
9.2%	43.7%	42.8%	25.9%	1.7%

15. Why do you think is the main risk factors of SRPs? (Multiple answers are possible.)

Downside risk	Market manipulation	Defaults of issuers	Others
76.2%	22.4%	8.3%	14.3%

16. Source of information for SRPs

Media	Brochures	Brokers	Internet	Term sheets
10.7%	26.4%	53.7%	5.7%	3.4%

17. How much are you satisfied with explanations by brokers?

Very satisfied	Satisfied	Neutral	Dissatisfied	Very dissatisfied
29.2%	57%	13%	0.6%	0.2%