Structured retail products: risk-sharing or risk-creation?*

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Abstract

Financial institutions have been issuing more complex structured retail products (SRPs) over time. Is risk-sharing the force behind this financial innovation? Is this innovation welfare-increasing? We propose a simple test for these questions. The test depends only on standard risk and return measures. If a given type of SRP is not based on risk-sharing and creates unbacked risks, we should observe an unusual negative relationship between risk and expected return across such products. We test this hypothesis using a sample of 1,847 SRPs and find that most products are risk-sharing devices, but a common type of SRP (autocallables) creates risks.

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1 Introduction

The market for structured retail products (SRPs) has burgeoned worldwide over the last two decades.[1] The growing literature on SRPs has found two complementary explanations for this. On the supply side, financial institutions earn high margins by issuing SRPs.[2] On the demand side, retail investors, with limited access to derivative markets, are attracted by the non-linear payoffs offered by SRPs (mainly capital guarantees).[3] However, one crucial question has been overlooked: do SRPs share or create risk?

Clever ways to share risk foster investment and raise welfare.[4] However, if institutions create (overpriced) unbacked-risk products to sell to retail investors, institutions profit on average, and investors lose on average, but they all hold more risk. From a social point of view, these financial innovations are undesirable.

It is, however, difficult to know whether a security shares pre-existing risk or generates new unbacked risk. A brute force method to address this question would require the regulator to map the risks embedded in each product into the financial institution's balance sheet and to evaluate the institution's hedging strategies and practices. This is naturally a cumbersome, time-demanding task. Our paper proposes a simple and quick test to evaluate whether financial products share or create risk.[5] The test requires only standard measures of expected return and risk of SRPs. Products that fail this test would raise a yellow flag for the regulator, who could then investigate the matter more thoroughly.

The test is based on a simple model with retail investors that cannot perfectly compute the expected excess return and risk of structured products. The model predicts that if the

[1] According to Shin (2022), the sales volume in the market for global equity-linked SRPs went from 50 billion dollars in 2001 to 250 billion dollars in 2015. According to Vokata (2023), global outstanding volume is estimated at $2 trillion in 2022.

[2] See, for instance, Stoimenov and Wilkens (2005), Benet et al. (2006), Henderson and Pearson (2011), Celerier and Vallee (2017), Henderson et al. (2020a), and Vokata (2021).

[3] See Sanjiv and Statman (2013), Sonsino et al. (2022), Calvet et al. (2022), and Kallio et al. (2022).

[4] As argued by Cochrane (2005, 56), "better risk sharing is much of the force behind financial innovation. Many successful securities can be understood as devices to share risks more widely". See also Duffie and Rahi (1995), Allen and Gale (2003), and Tufano (2003).

[5] We apply the test to SRPs, but it could also be applied to any financial product sold to unsophisticated investors.

issuance of a given type of SRP creates new unbacked risk, the expected excess return offered to investors will be negatively related to risk across SRPs of that type. This unusual negative relationship arises because, in the case of risk creation, more risk to the buyer implies the seller is also bearing more risk. Hence, issuers will demand higher prices to create and sell riskier products. On the other hand, if the issuance of a given type of SRP is based on risk-sharing, more risk is akin to lower marginal cost. Hence, the expected excess return offered to investors will be positively related to risk across SRPs of that type.

We apply our test to a novel dataset with hand-collected data on 1,847 different SRPs. These products were issued by the banks BNP Paribas, Credit Suisse, Citibank, Goldman Sachs, JPMorgan Chase, Morgan Stanley, and Banco XP and were distributed by the largest brokerage house in Brazil (XP Corretora) between 2017 and 2022. We sort the 1,847 SRPs into five types according to their payoff formulas. Expected returns and risks differ among products within a given type only due to differences in the underlying assets, dates the SRPs were issued, and their maturities.

Four of the five types pass our test. Among those SRPs, the relation between risk and expected return is positive. This result holds even when we control for market beta, implying that the remaining risk in those products has a positive market price.

The SRPs that pass our tests are simple products that combine call options or straddles with fixed-income investments. Our results imply that they are risk-sharing devices with features that attract individual investors.

The fifth type comprises autocallable SRPs. The main feature of these financial products is the existence of trigger conditions. If the underlying assets meet a trigger condition (for example, their prices cross predetermined strikes on predetermined dates), the contract terminates, and investors receive their capital and, usually, a generous return. Autocallable SRPs fail our test. Riskier products yield a lower return on average, implying that this complex security indeed pours new unbacked risk into the financial system and, as such, is undesirable.

As discussed by Shin (2022), financial institutions have been issuing more complex SRPs over time. According to his rich dataset, the share of Autocallable SRPs went from 1% of the global SRP market in 2002 to 30% in 2008, reaching a whopping 50% in 2015. The difficulties in hedging autocallable SRPs are well-known.[6]

Our findings imply that regulation is likely warranted (see Campbell, 2016). To the best of our knowledge, we are the first to call attention to the question of risk-sharing or risk-creation among SRPs. Investors in this growing market do not seem to understand all the characteristics of the products they are buying.[7] As Shin (2022) shows, the share of complex SRPs has only increased, casting doubt on the hope that the market will evolve to an efficient equilibrium by itself.

We contribute to the literature that investigates the effects of financial innovation in environments with unsophisticated investors (Gennaioli et al., 2012, Boz and Mendoza, 2014, Li et al., 2018, Parker et al., 2023). In particular, we directly contribute to the discussion about the growing market for structured retail products (Stoimenov and Wilkens, 2005, Benet et al., 2006, Henderson and Pearson, 2011, Sanjiv and Statman, 2013, Celerier and Vallee, 2017, Henderson et al., 2020a, Vokata, 2021, Calvet et al., 2022, Kallio et al., 2022, Vokata, 2023). Unlike these papers, our concern is not the high cost of SRPs, which has already been well-documented. If this were the sole issue, enhanced market competition could potentially address it, even in a market with unsophisticated retail investors. Our assertion is that the increasing complexity of certain SRPs is likely to represent an undesirable financial innovation (regardless of their pricing).

The remainder of the paper is organized as follows. Section 2 presents the test, Section 3 applies the test to our sample of SRPs, and Section 4 concludes.

[6]Kim and Lim (2019) write: "despite their popularity and influence on financial markets, the risk management of autocallable barrier reverse convertibles remains a critical issue." See also Cui et al. (2023).

[7]See Celerier and Vallee (2017), Vokata (2021), Vokata (2023) and, more generally, Merkoulova and Veld (2022).

2 The framework

Does the issuance of a given type of SRP pours new unbacked risk into the financial system? We now develop a quick test to this complex hypothesis.

The test is based on the following model. There are 2 periods and 2 types of agents: one bank (B) and a measure-one continuum of individuals (I). Agents consume C_i in the second period only. Their preferences are given by

$$U_i = E(C_i) - \gamma_i Var(C_i)$$

for $i \in \{B, I\}$, where $\gamma_i > 0$ are the risk-aversion coefficients for banks and individuals, respectively. Function U_i can be seen as a quadratic approximation of the expected utility of risk-averse agents. For banks, γ_B captures any cost of having undesired risk in the balance sheet.[8] Empirical research has shown that financial institutions try to hedge structured products (Henderson et al., 2020b) and that hedging is often costly (Entrop and Fischer, 2020; Avdiu and Unger, 2023). There is indeed literature on managing the risk of SRPs aimed at scholars and practitioners, suggesting that the risk of these products is a first-order issue.[9]

There is infinite supply of two assets: a risk-free one that pays a return normalized to zero; and an asset that represents a fully diversified market portfolio and yields a normally-distributed log return R_M.

Structured products A structured product is characterized by its correlation with market return β, its residual risk σ^2, and its expected excess return α. That is, the log return on

[8]Research has shown banks behave as risk-averse agents (e.g., Angelini, 2000). As argued by Froot and Stein (1998), this behavior might arise even if they have risk-neutral preferences owing to financial constraints.

[9]See, among others, Guillaume (2015), Kim and Lim (2019), Paletta and Tunaru (2022), and Cui et al. (2023).

structured product j is

$$R_j = \alpha_j + \beta_j R_M + \epsilon_j \tag{1}$$

where ϵ_j is normally distributed with mean 0 and variance σ^2. By construction, ϵ_j is uncorrelated with market return R_M.[10] Define the product excess return $r_j = R_j - \beta_j R_M$, given by

$$r_j = \alpha_j + \epsilon_j$$

Individuals' maximization problem It is difficult for the typical retail investor to estimate an SRP's expected return and volatility. To assess the risk and return of those financial products, one would need to estimate variances and covariances among the underlying assets and the market index and feed those estimates into Monte Carlo simulations – this is indeed what we do to run our test. Retail investors typically do not master those techniques. This is a problem for them because SRPs are likely designed to look more profitable and less risky than they really are — for example, with lower bounds on nominal returns.

The literature has explored the idea that retail investors are not equipped to evaluate newly-engineered securities. Carlin (2009) argues that many households who purchase retail financial products do not properly understand what they are buying and how much they are paying. The findings in Celerier and Vallee (2017) suggest that banks strategically use product complexity to cater to yield-seeking households by making product returns more salient and shrouding risk. Ammann, Arnold, and Straumann (2023) empirically show that asymmetric information between issuers and investors plays a key role in explaining the markups of structured products, and that issuance volumes are increasing in information asymmetry.[11] Moreover, financial advisors have incentives to overstate the benefits of SRPs — they receive selling commissions from issuers — and research indicates they respond to

[10]For many structured products, ϵ_j will not be independent of R_M owing to their non-linear payoffs. Consider for instance a product analogous to a call option on the market portfolio. If $R_M < 0$, we have $R_j = 0$ and, consequentially, the lower R_M, the higher ϵ_j. However, even in these cases, R_M and ϵ_j will be uncorrelated by construction.

[11]Gennaioli, Shleifer, and Vishny (2012) present a model where investors neglect certain risks when trading securities and show that as a result, security issuance is excessive.

these incentives (Egan et al., 2019).

Given all those findings, it is not surprising that retail investors overpay for SRPs, as shown by Stoimenov and Wilkens (2005), Henderson and Pearson (2011), Celerier and Vallee (2017), Vokata (2021) and Merkoulova and Veld (2022).

Accordingly, we make two assumption about agents' perceptions of risk and return. First, we assume that retail investors believe that the expected return of an SRP is

$$E\left(r_j\right) = \alpha_j + \Delta$$

with $\Delta \geq 0$. One possible reason for $\Delta > 0$ is that individuals overestimate the expected return of SRPs – after all, these products are tailored to entice retail investors. Another possibility is that individuals are willing to pay a premium Δ for some characteristics of an SRP – for example, the guarantee of non-negative nominal returns. Either way, a positive Δ leads individuals to pay high prices for SRPs, in accordance to the empirical evidence. For the purposes of this paper, both interpretations lead to the same implications.

With respect to risk, we model the asymmetric information problems that cloud the risk assessment of retail investors in a simple way: we assume the perceived variance of a product $\widetilde{\sigma}^2$ is

$$\widetilde{\sigma}^2 = \bar{\sigma}^2 + \phi\sigma^2$$

with $\bar{\sigma}^2 \geq 0$ and $\phi \in (0, 1)$. A value of ϕ below 1 implies that increases in the risk of an SRP are not fully perceived by individuals. This assumption seems reasonable within a group of SRPs with similar characteristics. The variance of an SRP's returns depends non-trivially on the interest rate and the variances and covariances of underlying assets and is not easily estimated.

We also assume that the residual risk ϵ_j is uncorrelated to individuals' consumption risk. In theory, individuals could be willing to buy a product that yields a low return to hedge their idiosyncratic consumption risk. However, the literature on SRPs does not support this reasoning. Moreover, for our empirical application, the idea of SRPs as hedges for idiosyncratic risk looks far-fetched.

Let q be the amount of an SRP purchased by an individual. The quantity q is chosen to maximize

$$U_I = (\alpha_j + \Delta)q - \gamma_I \widetilde{\sigma}^2 q^2 \tag{2}$$

Banks' maximization problem The bank has a technology to create an SRP with certain ϕ and Δ, given by the features of the product. The ability to create securities that look more profitable and less risky than they are would be captured by $\Delta > 0$ and $\phi < 1$. Knowing those parameters and the the demand from retail investors, the bank chooses α_j. A larger α_j raises the profit per unit sold but reduces the quantity purchased by individuals. If the structured product's risk is a hedge for risks held by the bank, its consumption at $t = 2$ is

$$C_B = -\alpha_j q + (\xi - q)\epsilon_j$$

plus some terms unrelated to the choice of α_j. The parameter ξ measures the exposure of the bank to the risk embedded in the SRP. In contrast, if the risk on the structured product is unrelated to the risks held by the bank, its consumption at $t = 2$ is

$$C_B = -\alpha_j q - q\epsilon_j$$

plus some terms unrelated to the choice of α_j.

Therefore, the bank maximizes

$$U_B = -\alpha_j q - \gamma_B \left[(\xi - q)^2 \sigma_j^2\right] \tag{3}$$

with $\xi > q$ when the product is a hedge for the bank (at the margin) and $\xi = 0$ if the product effectively creates risk.

2.1 Equilibrium

From (2), the first order condition for individuals with respect to q implies:

$$q = \frac{\alpha_j + \Delta}{2\gamma_I(\bar{\sigma}^2 + \phi\sigma^2)} \tag{4}$$

The demand for an SRP depends positively on its perceived expected return and negatively on its perceived risk.

Plugging the expression for q into (3) and taking the first order condition for the bank with respect to α_j yield

$$\alpha_j = -\frac{\Delta}{2} + \gamma_B\sigma^2(\xi - q) \tag{5}$$

where q is determined by the individuals demand. The expected return in influenced by Δ but also by the product's risk (σ^2).

One implication of (5) is that if $\gamma_B = 0$, risk does not affect the SRP price, and $\alpha_j = -\Delta/2$, implying that expected returns and risk should be uncorrelated.

We are now ready to state the model's key results. Proposition 1 shows results for structured products that share risk between individuals and the bank.

Proposition 1. *Suppose ξ is positive and large enough to imply that the structured product is a hedge for the bank. Then*

1. q is positive in the case $\Delta = 0$
2. α_j might be positive or negative
3. α_j is increasing in σ^2 for a given Δ

Proof See Appendix A.1.

When the product works as a hedge for the bank, there is trade even if individuals fully understand the asset's expected return ($\Delta = 0$). The bank is willing to offer agents a positive expected excess return α_j to eliminate some of the risks it bears. If Δ is positive, the bank can profit even more from selling the product and will choose a lower α_j. Inspection of (5) shows that the expected excess return might then be positive or negative.

In this case, a higher variance σ^2 is akin to a reduction in cost. More risk implies a higher benefit for the bank from selling the product, so the bank is willing to offer a higher expected excess return.

Results are different for structured products that create risk. Proposition 2 summarizes the model implications.

Proposition 2. *Consider the case $\xi = 0$. Then*

1. $q = 0$ in the case $\Delta = 0$
2. α_j must be negative
3. α_j is decreasing in σ^2 for a given Δ

Proof See Appendix A.2.

When the product risk is unrelated to the bank portfolio, there is no gain from trade. Selling the product implies that the bank and its clients bear more risk. If $\Delta = 0$, individuals do not buy the SRP. Banks and individuals that can accurately assess an asset's returns must be compensated for the risk they hold.

When $\Delta > 0$, a product that creates risk can be traded, and its expected excess return must be negative. The bank would never offer a positive expected excess return on a product that raises the risk it holds.

In this case, a higher variance σ^2 is akin to an increase in cost. Hence the bank offers a lower expected excess return for higher-risk products. As a result, individuals get a lower expected excess return from buying riskier assets.

Residual risk, in this case, can be seen as a by-product of building a complex asset that generates a large perceived return. Since holding this risk is costly to the bank, trade in the structured product is welfare-reducing.

A similar reasoning also applies to betting houses. They also issue lotteries with negative expected returns as they have to be compensated for the risk they hold.

One could argue that retail investors buy SRPs for the same reasons they buy bets: it is fun to bet (on sports or politics), and people like lotteries with high upsides. Research has indeed shown that individuals like lottery-like stocks.[12] However, this reasoning would apply to all kinds of SRPs, so it would not explain why we find opposite results for different groups of products. Moreover, among financial products, SRPs are not particularly fun and certainly not sold as being so. Last, the variance of an actuarially fair lottery is decreasing in the size of the jackpot, so it is at best unclear that the preference for skewed payoffs would lead agents to overpay for high-variance SRPs.

2.2 The test

Propositions 1 and 2 yield a test to distinguish between types of SRPs that share risk and those that create risk. Across products of a given type of SRP, a positive relation between residual risk and expected return is consistent with risk-sharing. Conversely, a negative association between risk and return, associated with expected returns below zero, is a sign of risk creation.

The test crucially depends on Δ and ϕ being the same across products of a given type. Hence, within each group of SRPs, there should be no difference in complexity, and expected returns and risk should vary simply due to differences in the underlying assets, dates of issuance, and maturities.

[12] See, for instance, Gompers and Metrick (2001); Kumar (2009); Conrad et al. (2014); Birru and Wang (2016).

3 Empirical evidence

We now apply our test to 5 different types of SRPs. We evaluate 1,847 SRPs issued by the banks BNP Paribas, Credit Suisse, Citibank, Goldman Sachs, JPMorgan Chase, Morgan Stanley, and Banco XP and distributed to Brazilian retail investors by the largest brokerage house in Brazil (XP Corretora) between 2017 and 2022.

Structured products are popular among retail investors in Brazil. At the beginning of 2021, Brazilian retail investors held 22 billion reais (4.4 billion dollars) in structure products issued by national and international banks. As a comparison, in the same period, Brazilian retail investors held 63 billion reais in treasury bonds (direct holding through brokerage houses).

For each of the 1,847 products, we hand-collected its brochure from the brokerage house website — it is an open-access portal in which anyone can visualize all products distributed since 2017.[13] A brochure describes the exact payoff rule for each product. We then estimate each product's expected excess return, total volatility, residual volatility, and market beta by estimating the characteristics of each underlying asset and simulating many trajectories for them — in the same spirit of Calvet et al. (2022).

3.1 Estimation procedure

We first estimate the underlying assets' parameters needed to simulate trajectories for all underlying assets. We use the 252 daily log returns ending one day before the structured product issuing date. For each underlying asset i we regress its daily excess log returns on the relevant market's excess log return and obtain its $\hat{\beta}_i$.[14] Using the residuals from these regressions we estimate $\hat{\Sigma}_i$, the variance-covariance matrix for the idiosyncratic shocks in

[13] The brochures are available at https://www.xpi.com.br/investimentos/coe/historico-emissoes/.

[14] Market returns and risk-free rates are selected according to where each underlying asset is traded. For stocks traded in Brazil, we use Ibovespa Index and BZAD1Y Index; for Europe, STOXX Europe 600 Index and EUR012M Index; for Japan, NKY Index and GJGB1 Index; for Norway, OBX Index and GTNOK1YR Index; for South Korea, KOSPI Index and GVSK1YR Index; for Switzerland, SMI Index and CTCHF1YR Govt; for the United Kingdom, UKX Index and GUKG1 Index; for the United States, S&P500 Index and GB12 Govt.

the underlying assets of each product (or the variance, in case the product has only one underlying asset).

For each product, we then simulate $N = 1000$ trajectories of its underlying asset(s) imposing that their daily log return are given by the CAPM:

$$\log \frac{P_{t,i}}{P_{t-1,i}} = r_f \Delta t + \hat{\beta}_i (r_{M,Sim,t} - r_f \Delta t) + \sqrt{\Delta t}\epsilon_{i,t} \qquad (6)$$

where r_f is the annual risk-free rate in the asset's country, $\Delta_t = 1/252$, and $\epsilon_{i,t}$ is a shock-term drawn from a Normal distribution with zero mean and variance $\hat{\Sigma}_i$. The daily simulated market return term ($r_{M,Sim,t}$) comes from

$$r_{M,Sim,t} = \left(0.06 - \frac{\sigma_M^2}{2}\right) \Delta t + \sqrt{\Delta t}\epsilon_{M,t} \qquad (7)$$

where we set the equity premium to 6%, σ_M is the historical market volatility and $\epsilon_{M,t}$ is sampled from a Normal distribution (in case the structured product is based on underlying assets traded on more than one market, we consider the markets' correlation). As before, the historical market volatility is estimated from the 252 log returns ending the day before the structured products' initial date.

After we simulate the N trajectories for the underlying assets of each structured product, we compute the product's return in each trajectory considering the product's exact payoff formula. For some products, the termination date depends on the trajectory of the underlying assets and may occur before its maturity. In case of early termination, we allocate the proceedings in a risk-free product yielding the forward rate (from the day it was terminated to the original maturity) implied by the (Brazilian) yield curve from one day before the structured products' starting date. Finally, we annualize the market and product returns in each trajectory, obtaining a vector of N paired annual returns for each product.

The product's expected excess return is given by the average of the annualized returns of the product across the N trajectories minus the return of the risk-free investment available for the investor on the issuing date. The product's volatility is given by the standard deviation of the annualized returns of the product across the N trajectories. The product's residual volatility and β are obtained by regressing the annualized structured product's return on the annualized market return across the N trajectories.

3.2 Five types of Structured Retail Products

The 1,847 products distributed by the brokerage house can be classified into 5 types. Each of those defines the product's payoff as a function of the behavior of its underlying assets during the product's duration. All 5 types are capital guarantee, a feature that, as shown by Calvet et al. (2022), attracts retail investors.

The key assumption for our tests is that parameters Δ and ϕ are constant within each product type. Indeed, across products of a given type, payoff formulas are the same, and products differ only in terms of the underlying assets, return parameters, and issuance and maturity dates. Celerier and Vallee (2017) measure the complexity of an SRP as a function of the payoff features that are embedded in the payoff formula of a product. Using their criteria, all products of a given type have the same level of complexity.

The 5 types are:

- Type 1 (637 products)
  - If the underlying asset depreciates during the period, the buyer receives zero return; if the underlying asset appreciates, the buyer receives a function of the asset return.
  - An example: Issuing date: 09/26/2017. Final date: 09/28/2020. Underlying asset: an ETF (SPDR Gold Shares) traded at NYSE that tracks the gold price. Payoff formula: if the price of the underlying asset on the final date is $x\%$ above its price on the issuing date, the buyer receives on the final date $(1+1.35\times x\%)V$, where V is the volume invested; if the price of the underlying asset on the final

date is below or equal its price on the issuing date, the buyer receives on the final date V.

- Type 2 (500 products):
  - If the underlying asset depreciates during the period, the buyer receives a fixed return; if the underlying asset appreciates, the buyer receives a function of the asset return.
  - An example: Issuing date: 04/26/2017. Final date: 04/26/2022. Underlying asset: S&P500. Payoff formula: if the price of the underlying asset on the final date is $x\%$ above its price on the issuing date, the buyer receives on the final date $(1.2 + x\%)V$, where V is the volume invested; if the price of the underlying asset on the final date is below or equal its price on the issuing date, the buyer receives on the final date $1.2V$.
- Type 3 (103 products):
  - If the underlying asset depreciates during the period, the buyer receives the inflation of the period; if the underlying asset appreciates, the buyer receives a function of the asset return plus the inflation of the period.
  - An example: Issuing date: 05/03/2019. Final date: 05/07/2024. Underlying asset: JP Morgan Global Total Return FT Index. Payoff formula: if the price of the underlying asset on the final date is $x\%$ above its price on the issuing date, the buyer receives on the final date $(1+x\%)(1+\pi\%)V$, where $\pi\%$ is the Brazilian inflation in the period (Ipca index) and V is the volume invested; if the price of the underlying asset on the final date is below or equal its price on the issuing date, the buyer receives on the final date $(1 + \pi\%)V$.
- Type 4 (128 products):

- The buyer is long in volatility, receiving a function of the underlying asset return if case it appreciates or depreciates during the period.
- An example: Issuing date: 09/17/2019. Final date: 09/17/2024. Underlying asset: S&P500. Payoff formula: if the price of the underlying asset on the final date is $x\%$ above its price on the issuing date, the buyer receives on the final date $(1 + x\%)V$, where V is the volume invested; if the price of the underlying asset on the final date is $x\%$ below its price on the issuing date, with $x < 30$, the buyer receives on the final date $(1+x\%)V$; however, if $x \geq 30$, the buyer receives $1.35V$.

- Type 5 (479 products):
  - A more complex product, usually called *Autocallable*; the termination date of the product is uncertain; there are in general 3 stocks under the product; the product return and the termination date depend on the joint trajectories of the underlying stocks.
  - An example: Issuing date: 03/31/2017. Final date: 04/01/2019. Observation dates: 09/29/2017, 03/29/2018, 09/28/2018, and 03/29/2019. Underlying assets: the stocks AAPL, FB, NFLX, traded at Nasdaq. Payoff formula: if on the n_{th} (1, 2, 3, or 4, in this sequence) observation date the prices of all three stocks are above their prices on the issuing date, the product is terminated and the buyer receives $V(1 + 0.0875n)$, where V is the volume invested; otherwise, it continues. If the product continues until the final date, the buyer receives V.

For Types 1-4, risk is easily hedgeable with standard market instruments (the SRPs look like call options or straddles). However, for Type 5, the Autocallable product, the risk from the payoff formula looks unusual and hard to hedge (see Kim and Lim, 2019 and Cui et al., 2023). For instance, in the example above, the best-case scenario for the issuer is that the product continues until the final date. In this case, the issuer keeps the invested capital for two years at a zero cost. However, if the product is terminated at some observation point, the issuer has to return the money to the investor and pay a high rate (8.75% per half-year). Moreover, the longer it takes to terminate, the worse for the issuer.

As a result, products of Type 5 are good for the issuer in case of adverse price shocks to one or more assets during the whole period. On the other hand, they are bad for the issuer if i) one or more assets are hit by negative price shocks early on, and ii) these adverse shocks are more than reversed by later positive shocks before the last observation date. This sort of risk does not look conventional. It is also difficult to think of some idiosyncratic consumption risk associated with the residual risk of Autocallable SRPs.

3.3 Risk-sharing or risk-creation?

We now test whether banks are creating risks when issuing each one of the 5 types of SRPs. In this case, according to Proposition 2, we should observe a negative relation between expected excess return and residual volatility and a negative expected excess return across the products of that type. Table 1 presents the distribution of these measures for each type of product.

[Table 1 about here]

Panel A of Table 1 presents the distribution of the expected return over the risk-free rate on the product issuing date. The mean and median expected excess return for all types are negative, indicating that these structured products are generally expensive to retail investors. Similar results were found by Stoimenov and Wilkens (2005), Henderson and Pearson (2011), Celerier and Vallee (2017), and Vokata (2021). The type with the lowest mean and median expected excess return is Type 5. Panel B presents the distribution of the total volatility. Type 3 presents the lowest mean and median volatility. Panel C presents the residual volatility, i.e., the standard deviation of the residual of the regression with the product return on the left-hand side and the marker return (if the bank is international, the S&P500; if the bank is Brazilian, the Ibovespa) on the right-hand side. Again, Type

3 presents the lowest mean and median residual volatility. Finally, Panel D presents the distribution of the market beta of this regression. In general, betas are not high.

Next, we investigate the relationship between expected excess return and risk across the products of each type. We first regress the expected excess return on the total volatility. We then regress the expected excess return on the market beta and the residual volatility to evaluate the relation between the expected excess return and the residual volatility controlled for the systematic risk of the product. We also control the regressions for bank-year fixed effects. Hence, we are comparing products issued by the same bank in the same year. Standard errors are clustered by bank. Table 2 presents the results.

[Table 2 about here]

Panels A, B, C, and D of Table 2 show a positive relation between expected excess return and risk for Type-1, Type-2, Type-3, and Type-4 products. Column 2 shows that SRPs with greater total volatility have greater expected excess return, and column 4 shows that both market beta and residual volatility are positively related to the expected excess return.

Results are different for the more complex Type 5 products (Autocallables). Column 2 of Panel E from Table 2 shows that SRPs of Type 5 with greater total volatility tend to offer lower expected excess returns to their buyers.[15] Decomposing the total volatility into market risk and residual volatility, we find that market risk, which is easily hedged by the issuer, is positively related to the expected excess return. However, the greater the residual volatility, the lower the expected excess return for the buyer.

Figure 1 allows a clear visualization of this difference. The top graph presents the scatter plot across all products of Types 1, 2, 3, and 4, relating i) the expected excess return orthogonal to market beta with ii) the residual risk orthogonal to market beta. The usual

[15] As explained in Section 3.2, if the Autocallable SRP is terminated before its maturity, we allocate the proceedings in a risk-free product yielding the forward rate (from the day it was terminated to the original maturity) implied by the (Brazilian) yield curve from one day before the structured products' starting date. Hence its expected return is well-estimated and is not upward-biased, as discussed by Vokata (2021).

positive relation is clear. The bottom graph, in turn, presents the scatter plot across products of Type 5. An unusual negative relation is also clear.

[Figure 1 about here]

According to our model, the negative relation between residual risk and expected excess return documented for products of Type 5 implies that these products pour additional unconventional risk into the system. Proposition 2 also predicts that in the case of risk-creation, the expected excess return to investors must be negative. As shown in Table 1, this is indeed true for Type 5 products but not for any other type. This reinforces our conclusions.

3.4 What explains different residual volatilities?

A fundamental assumption for our test is that different products within a given type of SRP have the same level of complexity, so retail investors have the same difficulty in evaluating their expected returns and risk. In other words, parameters Δ and ϕ must be constant within each product type. Since the payoff formula within each kind of SRP is the same, this seems a reasonable assumption. We now complement this reasoning by showing that the differences in volatilities across products within the same type are due to factors unrelated to complexity, such as the underlying assets' second moments and the interest rate.

Products of Type 1

There are 637 products of Type 1. For this type of product, if the underlying asset depreciates during the period, the buyer receives zero return; if the underlying asset appreciates, the buyer gets a function of the asset return. The underlying asset can be a single stock or an index.

The basic parameters that can affect the residual volatility of the return of this product are the volatility of the underlying asset's return, the beta of the underlying asset, and the duration of the product (years to maturity). By regressing the residual annual volatility of each of the 637 products on these variables, we can explain 68.47% of the variation of the dependent variable, as presented in Table 3.

[Table 3 about here]

Products of Type 2

There are 500 products of Type 2. For this type of product, if the underlying asset depreciates during the period, the buyer receives a fixed return; if the underlying asset appreciates, the buyer gets a function of the asset return. The underlying asset can be a single stock or an index.

As for Type 1, the basic parameters that can affect the residual volatility of the return of Type 2 products are the volatility of the return of the underlying asset, the beta of the underlying asset, and the duration of the product (years to maturity). By regressing the residual annual volatility of each one of these 500 products on these variables, we can explain 58.91% of the variation of the dependent variable, as presented in Table 4.

[Table 4 about here]

Products of Type 3

There are 103 products of Type 3. For this type of product, if the underlying asset depreciates during the period, the buyer receives its money corrected by an inflation index; if the underlying asset appreciates, the buyer gets a function of the asset return plus the period's inflation. The underlying asset can be a single stock or an index.

As for Types 1 and 2, the basic parameters that can affect the residual volatility of the return of Type 3 products are the volatility of the return of the underlying asset, the beta of the underlying asset, and the duration of the product (years to maturity). By regressing the residual annual volatility of each of these 103 products on these variables, we can explain 71.67% of the variation of the dependent variable, as presented in Table 5.

[Table 5 about here]

Products of Type 4

There are 128 products of Type 4. For this product type, the buyer is long in volatility, receiving a function of the underlying asset return if it appreciates or depreciates during the period. The underlying asset can be a single stock or an index.

As for Types 1, 2, and 3, the basic parameters that can affect the residual volatility of the return of Type 4 products are the volatility of the return of the underlying asset (although, now, the direct effect of this parameter is on the expected return of the product), the beta of the underlying asset and the duration of the product (years to maturity). By regressing the residual annual volatility of each of these 103 products on these variables, we can explain 40.15% of the variation of the dependent variable, as presented in Table 6.

[Table 6 about here]

Products of Type 5

Finally, there are 479 Type 5 (autocallable) SRPs, the most complex product in our sample. The termination date of this product is uncertain; there is more than one stock under the product (in general three or four); the product pays a fixed pre-defined return if the product is terminated before the final (expiration) date or zero return if the product goes until the final date; whether the product terminates before the final date depends on the joint trajectories of the underlying stocks.

The basic parameters that can affect the residual volatility of the return of this product are: the number of stocks under the product; the individual volatilities of the stocks; their correlation and betas; and the duration of the product (years to maturity). Moreover, since banks offer fixed returns (the 8.75% in the example above) that are higher (lower) in periods when the risk-free rate is higher (lower), year dummies can also explain the volatility across products of Type 5.[16] As the following table shows, we can explain 74.04% of the variation of the dependent variable, as presented in Table 7.

[Table 7 about here]

3.5 Controlling for upside and downside betas

In Section 3.3 we regress the product expected excess return on its market beta and residual volatility. As described in Section 3.1, the product's beta and residual volatility are computed by regressing the annualized structured product's return on the annualized market return across the N simulated trajectories:

$$r_i = \alpha + \beta r_i^m + \epsilon_i,\ i = 1, ..., N$$

However, since the relation between the return of a typical structured product and the market return may be non-linear (as in the case of options), we could estimate upside and downside market betas and the residual volatility by running

$$r_i = \alpha + \beta_{up} Max \left\{ r_i^m, 0 \right\} + \beta_{down} Min \left\{ r_i^m, 0 \right\} + \epsilon_i,\ i = 1, ..., N$$

Then, we could regress the product expected excess return on its market upside and downside betas and residual volatility. This does not significantly affect our results, as Table

[16] For instance, in periods of low risk-free rate, the product fixed return is also low, say, 2%; hence, the product return can be either 0 or 0.02, implying a lower volatility. In turn, in periods of high risk-free rate, the product fixed return is also high, say, 8%; hence, the product return can be either 0 or 0.08, implying a higher volatility. The risk-free rate in Brazil varied a lot in our sample period, going from 12% p.y. in 2017 to 2% p.y. in 2020 and back to 9% in 2022.

8 shows. We continue to observe a negative relation between the expected excess return of the product and its residual volatility only for Type 5.

[Table 8 about here]

4 Conclusion

There is risk in productive operations. Financial markets create ways to share this risk with investors, who receive a premium. This is the beauty of financial markets.

However, our results for complex SRPs imply that financial agents are creating unbacked risk and selling it to investors. Both sides are getting riskier portfolios with no extra return. This is socially undesirable and occurs in equilibrium because buyers cannot fully evaluate the complex product. This side of financial markets is not beautiful. There is nowadays a lot of negative sentiment toward financial markets. Curbing their ugly side might help avoid a backlash that could hurt their productive role.

The issue we raise is not simply about how expensive SRPs, in general, are — which was already well-documented. Were this the only problem, increasing market competition would likely resolve that, even in an environment with naive retail investors. The claim we bring forth is that the escalating complexity of some SRPs is an undesirable financial innovation regardless of its (implicit) price.

The regulation mandates that packaged foods contain a Nutrition Facts label. This entails a cost to food producers since one does not need to know the amounts of calories, fat, and sugars in the ingredients to bake a cake. In contrast, financial institutions would face virtually no cost to inform consumers about their products' expected return and risk – they surely calculate these numbers when designing the product. The legislation could mandate them to inform potential buyers. We argue that the potential to reduce the traded volume of some types of structured products should be seen as a feature, not a bug of the regulation.

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A Proofs

A.1 Proof of Proposition 1

Solving for q using (4) and (5) yields

$$q = \frac{1}{\gamma_B \sigma^2 + 2\gamma_I(\bar{\sigma}^2 + \phi\sigma^2)} \left(\frac{\Delta}{2} + \gamma_B \sigma^2 \xi \right) \tag{8}$$

Then, solving for α_j leads to

$$\alpha_j = -\frac{\Delta}{2} + \frac{\gamma_B \sigma^2}{\gamma_B \sigma^2 + 2\gamma_I(\bar{\sigma}^2 + \phi\sigma^2)} \left(2\gamma_I(\bar{\sigma}^2 + \phi\sigma^2)\xi - \frac{\Delta}{2} \right) \tag{9}$$

First statement Imposing $\Delta = 0$ and solving for q yields

$$q = \frac{\gamma_B \sigma^2 \xi}{\gamma_B \sigma^2 + 2\gamma_I(\bar{\sigma}^2 + \phi\sigma^2)} > 0$$

Second statement Inspecting (9) shows that $\alpha_j > 0$ when Δ is small and $\alpha_j < 0$ when Δ is large.

Third statement We need to show that the derivative of α_j in (9) with respect to σ^2 is positive. To ease presentation, define C_1 and C_2 as

$$\begin{aligned} C_1 &= \frac{\gamma_B \sigma^2}{\gamma_B \sigma^2 + 2\gamma_I(\bar{\sigma}^2 + \phi\sigma^2)} \\ C_2 &= 2\gamma_I(\bar{\sigma}^2 + \phi\sigma^2)\xi - \frac{\Delta}{2} \end{aligned}$$

so

$$\alpha_j = -\frac{\Delta}{2} + C_1 C_2$$

and

$$\frac{d\alpha_j}{d\sigma^2} = \frac{dC_1}{d\sigma^2} C_2 + \frac{dC_2}{d\sigma^2} C_1$$

It is easy to see that $dC_2/d\sigma^2$ and C_1 are positive. Since $\xi > q$, by assumption, (8) implies that C_2 is positive. Simple differentiation shows that $dC_1/d\sigma^2$ is positive as well.

A.2 Proof of Proposition 2

First statement It follows directly from plugging $\Delta = 0$ and $\xi = 0$ into (8).

Second statement It follows directly from plugging $\xi = 0$ into (9).

Third statement Simple differentiation shows that

$$\frac{d\left(\frac{\gamma_B \sigma^2}{\gamma_B \sigma^2 + 2\gamma_I(\bar{\sigma}^2 + \phi\sigma^2)}\right)}{d\sigma^2} > 0$$

Hence (9) is decreasing in σ^2 when $\xi = 0$.

B Figures and Tables

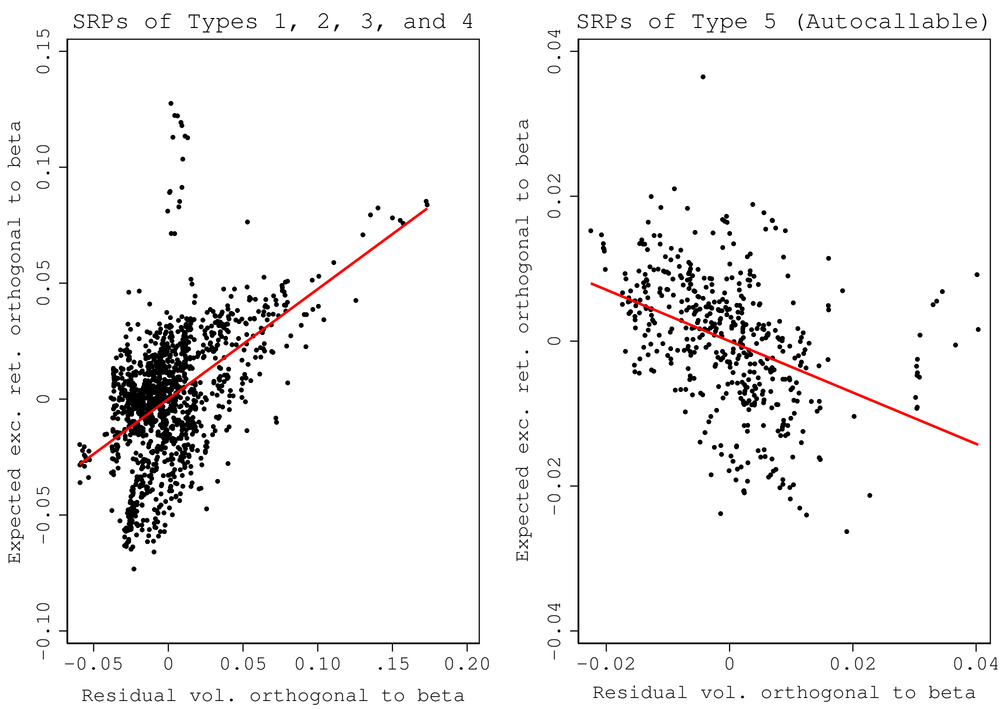

Figure 1: Relation between expected excess return and residual volatility

This figure shows the relation between expected excess return and volatility across the SRPs of Types 1, 2, 3, and 4 (left plot) and the SRPs of Type 5 (right plot). The relation is controlled for the market beta of the SRPs. That is, on the y-axis we have the residuals of a regression of expected excess returns on market beta and on the x-axis we have the residuals of a regression of residual volatility on market beta.

Table 1: Distribution of expected excess return and risk across the 1,847 products

This table presents the distribution across the SRPs of their expected excess return, total volatility, residual volatility, and market beta. These measures are estimated using the exact payoff formula of each product contained in its brochure and simulating many trajectories for its underlying asset(s). We described the estimation procedure in Section 3.1.

Panel A: Expected excess return (%, per year)

	# products	Mean	1 pct	25 pct	50pct	75 pct	99 pct
Type 1	637	-2.15	-8.92	-5.78	-2.51	0.99	6.96
Type 2	500	-1.09	-5.45	-2.55	-1.11	0.09	7.66
Type 3	103	-1.21	-3.33	-2.59	-1.84	0.00	4.16
Type 4	128	-1.05	-5.10	-2.90	-1.59	0.63	3.65
Type 5	479	-2.56	-4.88	-3.12	-2.47	-1.90	-0.76

Panel B: Return volatility (%, per year)

	# products	Mean	1 pct	25 pct	50pct	75 pct	99 pct
Type 1	637	6.99	1.80	4.17	6.76	9.29	19.36
Type 2	500	4.02	0.74	2.32	4.07	5.45	8.37
Type 3	103	3.79	1.73	2.72	3.43	4.48	8.73
Type 4	128	6.08	2.28	4.44	5.85	8.01	10.23
Type 5	479	4.70	2.67	3.99	4.64	5.35	7.75

Panel C: Return residual volatility (%, per year)

	# products	Mean	1 pct	25 pct	50pct	75 pct	99 pct
Type 1	637	6.20	1.79	4.02	5.44	7.92	18.65
Type 2	500	3.65	0.49	2.03	3.80	4.82	8.16
Type 3	103	3.49	1.67	2.38	3.19	3.97	8.51
Type 4	128	4.82	2.16	3.44	5.15	6.17	7.23
Type 5	479	4.45	2.44	3.63	4.44	5.07	7.68

Panel D: Market beta

	# products	Mean	1 pct	25 pct	50pct	75 pct	99 pct
Type 1	637	0.32	-0.28	0.07	0.21	0.41	1.53
Type 2	500	0.17	-0.14	0.04	0.13	0.27	0.81
Type 3	103	0.14	0.03	0.05	0.13	0.18	0.54
Type 4	128	0.31	0.05	0.25	0.31	0.38	0.83
Type 5	479	0.20	0.04	0.10	0.15	0.27	0.63

Table 2: Relation between expected excess return and risk

This table presents regressions across the SRPs of the expected excess return on the total volatility and of the expected excess return on the market beta and the residual volatility. In columns 2 and 4 we include bank-year fixed-effects. SPRs are divided by type. Standard errors are clustered by bank and the t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

Panel A: Type 1	Dependent variable: Expected excess return			
	(1)	(2)	(3)	(4)
Total volatility	0.924***	0.965***		
	(7.92)	(8.68)		
Market beta			0.062***	0.064***
			(20.98)	(30.50)
Residual volatility			0.730***	0.694***
			(8.81)	(29.59)
Constant	-0.086***	-0.089***	-0.087***	-0.085***
	(-12.95)	(-11.44)	(-17.74)	(-54.33)
Bank-year F.E.	No	Yes	No	Yes
Obs	637	637	637	637
Adj-R2	72.30%	80.03%	83.41%	91.68%

Panel B: Type 2	Dependent variable: Expected excess return			
	(1)	(2)	(3)	(4)
Total volatility	0.660***	0.631***		
	(9.16)	(8.13)		
Market beta			0.020	0.036***
			(0.64)	(5.02)
Residual volatility			0.605***	0.534***
			(4.68)	(4.62)
Constant	-0.038***	-0.036***	-0.036***	-0.037***
	(-12.33)	(-11.61)	(-7.32)	(-11.89)
Bank-year F.E.	No	Yes	No	Yes
Obs	500	500	500	500
Adj-R2	30.76%	76.85%	29.06%	78.19%

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Panel C: Type 3	Dependent variable: Expected excess return			
	(1)	(2)	(3)	(4)
Total volatility	0.864***	0.824***		
	(5.98)	(23.24)		
Market beta			0.086***	0.069***
			(10.96)	(6.39)
Residual volatility			0.596***	0.684***
			(5.95)	(23.26)
Constant	-0.044***	-0.043***	-0.044***	-0.045***
	(-7.49)	(-29.59)	(-7.45)	(-30.47)
Bank-year F.E.	No	Yes	No	Yes
Obs	103	103	103	103
Adj-R2	62.5%	87.04%	74.44%	79.85%

Panel D: Type 4	Dependent variable: Expected excess return			
	(1)	(2)	(3)	(4)
Total volatility	0.794***	0.829**		
	(32.19)	(5.70)		
Market beta			0.062*	0.035**
			(2.78)	(5.02)
Residual volatility			0.708***	1.047***
			(12.65)	(19.20)
Constant	-0.059***	-0.061***	-0.064***	-0.072***
	(-12.82)	(-6.89)	(-9.75)	(-8.76)
Bank-year F.E.	No	Yes	No	Yes
Obs	128	128	128	128
Adj-R2	59.16%	86.85%	53.05%	87.96%

Panel E: Type 5	Dependent variable: Expected excess return			
	(1)	(2)	(3)	(4)
Total volatility	-0.256**	-0.526***		
	(-2.58)	(-4.74)		
Market beta			0.024***	0.024***
			(3.90)	(4.29)
Residual volatility			-0.354**	-0.537***
			(-2.54)	(-10.19)
Constant	-0.014***	-0.001	-0.015**	-0.006**
	(-3.15)	(-0.16)	(-3.00)	(-2.45)
Bank-year F.E.	No	Yes	No	Yes
Obs	479	479	479	479
Adj-R2	7.70%	34.60%	20.56%	41.37%

Table 3: What explains different residual volatilities? - Type 1

This table presents regression of the residual annual volatility of each one of the 637 Type 1 products on the volatility of the underlying asset, the beta of the underlying asset and the duration of the product (years to maturity). Standard errors are clustered by bank and the t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	Dependent variable: Type 1 products volatility			
U.A. vol	0.372***			0.247***
	(23.87)			(17.36)
U.A. beta		0.072***		0.049***
		(26.33)		(18.84)
duration			-0.003**	-0.005***
			(-2.39)	(-7.43)
constant	0.031***	0.030***	0.074***	0.042***
	(18.95)	(19.16)	(13.58)	(12.95)
Obs	637	637	637	637
R2	47.29%	52.19%	1.00%	68.47%

Table 4: What explains different residual volatilities? - Type 2

This table presents regression of the residual annual volatility of each one of the 500 Type 2 products on the volatility the underlying asset, the beta of the underlying asset and the duration of the product (years to maturity). Standard errors are clustered by bank and the t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	Dependent variable: Type 2 products volatility			
U.A. vol	0.168***			0.181***
	(11.95)			(17.43)
U.A. beta		0.028***		0.028***
		(15.59)		(19.48)
duration			-0.002**	-0.003***
			(-3.27)	(-6.29)
constant	0.023***	0.022***	0.049***	0.024***
	(18.20)	(19.01)	(12.78)	(12.95)
Obs	500	500	500	500
R2	22.29%	32.78%	2.10%	58.91%

Table 5: What explains different residual volatilities? - Type 3

This table presents regression of the residual annual volatility of each one of the 103 Type 3 products on the volatility of the underlying asset, the beta of the underlying asset and the duration of the product (years to maturity). Standard errors are clustered by bank and the t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	Dependent variable: Type 3 products volatility			
U.A. vol	0.343***			0.225***
	(10.85)			(7.71)
U.A. beta		0.057***		0.038***
		(10.71)		(7.82)
duration			-0.002	-0.002
			(-1.09)	(-1.58)
constant	0.014***	0.013***	0.046***	0.016***
	(6.50)	(6.32)	(4.48)	(2.71)
Obs	103	103	103	103
R2	53.82%	53.19%	1.16%	71.67%

Table 6: What explains different residual volatilities? - Type 4

This table presents regression of the residual annual volatility of each one of the 128 Type 4 products on the volatility of the underlying asset, the beta of the underlying asset and the duration of the product (years to maturity). Standard errors are clustered by bank and the t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	Dependent variable: Type 4 products volatility			
U.A. vol	-0.059			0.192***
	(-1.12)			(3.76)
U.A. beta		0.023***		0.033***
		(7.30)		(9.00)
duration			-0.000	-0.008
			(-0.12)	(-2.56)
constant	0.050***	0.034***	0.050***	0.061***
	(22.85)	(15.07)	(2.64)	(3.96)
Obs	128	128	128	128
R2	0.99%	29.97%	0.01%	40.15%

Table 7: What explains different residual volatilities? - Type 5

This table presents regression of the residual annual volatility of each one of the 479 Type 5 products on the number of stocks under the product, the individual volatilities of the stocks, their mean correlation and mean betas, the duration of the product (years to maturity) and year dummies. Standard errors are clustered by bank and the t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	Dependent variable: Type 5 products volatility						
# of stocks	0.002***						0.001
	(4.41)						(1.46)
U.A. mean vol		0.015***					0.011***
		(3.77)					(2.96)
U.A. mean corr.			0.005*				0.012***
			(1.77)				(6.23)
U.A. mean beta				0.013***			-0.002
				(9.78)			(-1.49)
duration					-0.001**		0.001***
					(-2.34)		(4.81)
year F.E.						yes	yes
constant	0.035***	0.041***	0.445***	0.029***	0.048***	0.044***	0.024***
	(16.93)	(35.15)	(73.61)	(18.18)	(31.48)	(143.76)	(8.61)
Obs	479	479	479	479	479	479	479
R2	3.91%	2.89%	0.71%	16.71%	1.13%	58.69%	74.04%

Table 8: Controlling for upside and downside market betas

This table presents regressions across the SRPs of the expected excess return on the market upside and downside betas and the residual volatility. All columns include bank-year fixed-effects. SPRs are divided by type. Standard errors are clustered by bank and the t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	Dependent variable: Expected excess return				
	Type 1	Type 2	Type 3	Type 4	Type 5
Market upside beta	0.041***	0.042	0.032***	0.032***	-0.018***
	(8.96)	(1.65)	(4.22)	(11.19)	(-5.13)
Market downside beta	0.030***	0.024***	0.065***	-0.014	0.022***
	(6.13)	(5.83)	(3.31)	(-1.96)	(10.73)
Residual volatility	0.681***	0.436**	0.624***	0.925***	-0.477***
	(22.24)	(3.27)	(15.35)	(15.23)	(-6.73)
Constant	-0.084***	-0.037***	-0.045***	-0.067***	-0.010***
	(-36.87)	(-8.90)	(-28.36)	(-14.86)	(-3.53)
Bank-year F.E.	Yes	Yes	Yes	Yes	Yes
Obs	637	500	103	128	479
Adj-R2	91.61%	78.39%	90.00%	85.29%	52.70%