The Rise of Specialized Financial Products*

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Abstract

The variety of financial products available for firms to raise funds has expanded rapidly in recent decades. This paper studies the role of innovations that introduce specialized financial products using a combination of granular data and a parsimonious model of security issuance. We present three key findings. First, differential product adoption across firms explains most of the observed variation in the amounts of funds raised. Second, firms that adopt new products are more successful in raising funds. Third, the funds raised from new financial products are often sourced from numerous highly specialized products, each used by only a few firms.

Keywords: innovation; financial products; specialization.

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1 Introduction

Access to external funding is essential for firms to support growth and invest in projects. Firms are not indifferent to their capital structure (Colla, Ippolito and Li, 2013; Rauh and Sufi, 2010), and numerous innovations have expanded the set of financial products available for firms to issue. Yet, we show that firms in some sectors issue only a narrow set of common financial products, such as stocks and bonds, while firms in other sectors issue a broad variety of products, most of which are highly specialized.

Financial products specialized for certain sectors can better align with issuers' specific funding needs, helping firms raise more capital at lower cost (Lerner, 2006). Alternatively, firms may issue specialized products primarily to differentiate themselves from competitors and attract new investor pools (Tufano, 2003), potentially at the expense of the funding they are able to raise. This prompts key questions: Does what firms issue help explain how much funding they raise? And what role do specialized products play?

In this paper we address these questions, highlighting how the introduction of new financial instruments has broadened the variety of specialized products available to firms. To this end, we combine granular data on security issuance with a parsimonious model of firms' decisions over which financial products to issue. When firms decide to raise funds by issuing securities, they must choose from a set of available financial products. Firms use those financial products that provide the most favorable payoffs, while accounting for demand, competitive forces, and risk. Leveraging the model's structure, we show that the variety of new financial products plays a significant role in the allocation of funding among firms.[1] Our main empirical results support a mechanism through which most financial product innovations give rise to horizontally differentiated products that are well-suited to specific firms and sectors.

Our analysis is based on comprehensive data on security issuances by non-financial firms in the U.S. between 1985 and 2014, from the Security Database Company (SDC). We begin by building on the SDC's categorization of securities to distinguish between financial products. Over this period, a broad set of financial products was issued by firms across various sectors of the economy. These include well-established products, such as *Common Shares* and *Global Notes*, as well as less familiar ones, like *Sinking Fund Debentures*. Notably, we document that the wide variety of products is largely driven by the introduction of new financial products

[1]This is in line with findings in a recent literature on innovation in non-financial products which emphasizes that expanding product variety is a key mechanism for firms' growth. See, for example, Bresnahan and Gordon (2008); Broda and Weinstein (2006); Garcia-Macia, Hsieh and Klenow (2019); Braguinsky, Ohyama, Okazaki and Syverson (2021); Hsieh, Klenow and Shimizu (2021); Neiman and Vavra (2023).

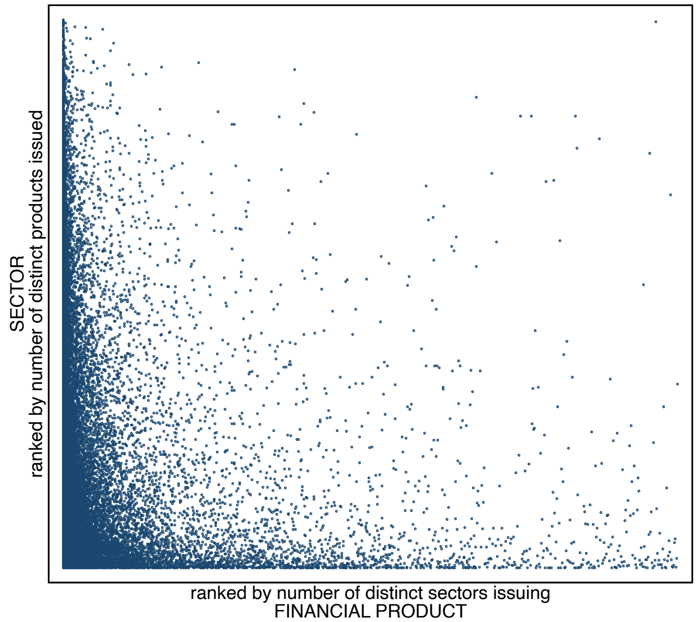
– identified by their first issuance date – which expanded the set available to firms from approximately 150 in 1985 to about 750 in 2014. These new financial products represent an important source of external financing for firms, with the median product having an issuance size comparable to that of the median syndicated loan.

To understand whether new financial products are meaningfully distinct, we propose a measure to quantify their degree of novelty. For this, we extract information about each financial product from articles published in a comprehensive online financial dictionary, Investopedia, and generate product descriptions using natural language processing methods (Manning, Raghavan and Schütze, 2008). This textual analysis allows us to create systematic measures of similarity between the descriptions of all pairs of products in our sample. Using these pairwise similarity measures, we then calculate the degree of novelty of each new financial product relative to the closest product already on the market. Our findings indicate that, while innovation in financial products is largely incremental – since many new products appear to build upon existing ones – it is also evident that new products possess distinctly identifiable characteristics.

Financial products exhibit significant variation in their adoption across firms in specific sectors. Figure 1 shows the allocation of products to sectors. Each observation indicates that at least a firm in a given sector has issued a given financial product at least once over the period 1985-2014. Sectors are ranked from those that use the most products, such as *Electric Services* or *Petroleum and Natural Gas*, to those that use the fewest products, such as *Confectionery* or *Book Printing*. Similarly, products are ranked from those used in the most sectors to those used in the fewest. A relatively small number of financial products, such as *Common Shares* and *Notes* are issued widely, by firms across most sectors. The majority, however, are used only within a few distinct sectors. This pattern is particularly pronounced in new products: nearly 50% of new products are used only by firms within a single sector, compared to only 15% for older products. This suggests that new financial products are more likely to be tailored to the specific needs of firms in different sectors.

We construct a simple conceptual framework that guides our analysis. Firms select financial products from a menu of products and issue securities that are acquired by investors. A financial product is a technology that converts firms' idiosyncratic and sector-specific risk factors into a stochastic payoff for investors. The optimal security design has been extensively studied in the literature which explicitly models the role of information asymmetries, transaction costs and other frictions (see Allen and Barbalau (2024) for an extensive survey). To capture the variety of products observed in the data in a flexible and tractable way, we

Figure 1: Allocation of Financial Products to Sectors



Notes: The figure shows the pairs of security type and sector for which we observe at least one issuance. We rank security types from the one used by the most sectors to the one used by the fewest sectors. Similarly, we rank sectors in the order of the number of securities issued. Each dot in this figure indicates that at least a firm in a given sector has issued a given security type at least once over the period 1985-2014.

adopt a broader perspective without taking a stance on a particular friction. In our analysis, products are characterized by different levels of productivity. A higher-productivity product improves investors' expected utility by either increasing the expected payoff and/or decreasing the variance of the payoff. We allow for heterogeneity in the productivity of financial products across sectors to accommodate the possibility that financial products may be horizontally differentiated.

In this framework, firms have two motives when choosing which product to issue. Firms prefer financial products with higher-productivity because these contracts are more valuable to investors and generate more proceeds, *ceteris paribus*. However, higher-productivity products attract more issuers, ultimately limiting each firm's ability to raise external funds. To counteract this, issuers select financial products that help them differentiate from competitors. Indeed, anecdotal evidence suggests that firms consider market conditions when issuing securities, and that a thin supply with reduced competition can improve issuance terms.[2]

The tension between the productivity of financial products and competitive forces is cen-

[2] "Corporate Market Experiences Growing Concerns About Supply" (WSJ, 1998).

tral to the model and results in the issuance of multiple products with varying productivity in equilibrium. Unlike the traditional view that financial innovation creates value by completing markets through spanning, products in our model are valuable because they can have high productivity for firms in certain sectors.

We use the framework to tease out the role that the differential adoption of new, specialized financial products might play in explaining differences in firms' ability to raise external funding. To this end, we derive functional forms for the total amount of funds that firms in a given sector raise in equilibrium. We show that the (log) total proceeds generated in a given sector can be decomposed into three components. The first component represents the average productivity of financial products issued by a sector in equilibrium. The model implies that sectors in which firms issue higher-productivity products have higher proceeds. A second component captures the degree of competition among firms issuing securities, as well as firms' risk factors. The third component captures various determinants of investor demand.

In our main empirical analysis we estimate the relative importance of these margins. The decomposition depends on variables that we directly observe in our main data set and parameters that we estimate from data we draw from sources like Compustat. While we do not observe the sector-specific productivity of each product and cannot directly quantify the overall importance of this factor, we use the structure of the model to quantify the contribution of financial products productivity in explaining the variation in proceeds across sectors. Using methods like those of Eaton, Kortum and Kramarz (2004), we find that changes in the average productivity of financial products explain almost two-thirds of the variance in proceeds across sectors. The remaining variation results mainly from changes in the degree of competition among firms and differences across risk factors. Differences in investor demand across sectors play a smaller role in explaining variation in the amounts of funds raised.

The last part of the paper investigates the mechanisms that drive changes in the average productivity of financial products. While we cannot establish causality, our analysis provides supporting evidence that new financial products contributed to an increase in overall average productivity. Most importantly, we distinguish new products as specialized or standardized based on the number of sectors that use them, and show that the introduction of specialized new products had the greatest effect on differences in average productivity across sectors. Standardized new products, those that are broadly used across multiple sectors, often have a large effect on the overall amount of funds raised, but have little effect on the differences in firms' ability to raise funds. Our results suggest that innovation in financial products results from efforts to create specialized products that cater specifically to the financing needs of select firms and sectors. Thus, our analysis suggests that financial products exhibit "love-for-variety" effects and innovation in financial markets resembles innovation in consumer markets, where progress is characterized by an increasing variety of specialized products tailored to specific needs.

Throughout our analysis, we treat firms' decisions to raise funds through securities contracts as given. While firms can also raise funds through bank loans or a combination of both (Rauh and Sufi (2010), Denis and Mihov (2003)), issuing securities often serves as a more significant source of funding. Indeed, Faria e Castro, Jordan-Wood and Kozlowski (2024), using recent Y-14 data, show that for firms with access to security markets, bond issuances tend to be significantly larger than loans. This finding is consistent with Schwert (2019) that provides evidence that borrowing from banks is more expensive than borrowing from the market. These findings suggest that firms prefer to issue securities when not otherwise constrained. Thus, understanding the role of financial products in facilitating firms' access to funds is crucial, even though less-successful firms in security markets may substitute security issuances for bank loans.

Related Literature – Our quantitative work on measuring the contribution of financial products to firms' ability to raise capital, along with our modeling of these products, is relevant to the literature on firms' capital structure, the measurement of innovation and economic growth.

The heterogeneity in firms' security issuance decisions that we document reinforces the long-standing view that firms are not indifferent to their capital structure (Graham and Leary, 2011; Frésard and Phillips, 2022). While a large body of literature examines firms' optimal capital structure, particularly the choice between debt and equity, some studies—such as Colla et al. (2013) and Rauh and Sufi (2010)—take a more focused approach, predicting public firms' debt structure based on attributes like size, leverage, and growth opportunities. We advance this research by providing a more granular analysis that quantifies the role of financial product adoption in firms' success in raising funds.

With the introduction of new financial products driving a substantial fraction of corporate security issuances in our sample, quantifying innovations becomes particularly important. Measuring innovation is a difficult task in any context (Bryan and Williams, 2021; Kelly, Papanikolaou, Seru and Taddy, 2021; Kogan, Papanikolaou, Seru and Stoffman, 2017), and especially when it comes to financial products (Lerner and Tufano, 2011; Lerner, Seru, Short and Sun, 2022). Traditional measures of innovative activity, such as R&D spending and patenting, are not readily available in the financial sector. Recently, Lerner, Seru, Short and Sun (2022) have shown that patented financial innovations, primarily driven by IT and other non-financial firms, are largely focused on products aimed at household investors and borrowers. An alternative approach, which may be better suited to capturing products that are traditionally non-patentable, is to develop measures that assess the novelty of financial products as they are introduced. For instance, Lerner (2006) constructs a measure of financial innovation based on news stories in the Wall Street Journal. Innovations span not only the underwriting of novel securities but also advances in asset management, retail banking, and mortgages, with the Wall Street Journal implicitly prioritizing products innovative enough to warrant coverage. Our approach is related but diverges by relying on listings of new securities from the SDC, as suggested by Tufano (2003), to classify products distinct from existing ones as innovations. Most notably, we develop a new measure of innovation that captures a product's novelty relative to other products in the market using natural language processing techniques. This measure takes the form of a novelty index that tracks financial product innovations, including both significant departures from existing securities and minor variations.

A larger body of work focuses on assessing the impact of financial innovation on investors. Theoretical work that highlights harms to investors includes Biais, Rochet and Woolley (2015), Caballero and Simsek (2013), Gennaioli, Shleifer and Vishny (2012), and Thakor (2012). Empirical work has typically focused on the harms investors have suffered from the introduction of particular financial products like SPARQS (Henderson and Pearson, 2011), structured notes (Bergstresser, 2008), or auction rate securities (Han and Li, 2010). The prevailing message of this literature is that investment banks benefit from innovative financial products at the expense of investors. While Calvet, Célérier, Sodini and Vallée (2021) present a more optimistic view, arguing that banks introduce innovative product features to attract investor pools that might otherwise avoid financial markets, their analysis remains focused on the impact for investors. Our focus differs from previous literature, as we concentrate on innovations in financial products for corporate firms, and quantify how these innovations contribute to issuers' ability to raise funds.

Our quantitative findings leverage insights from a parsimonious model we propose to rationalize the cross-section of security designs observed in our sample. Optimal security design has been the focus of an extensive research (Allen and Gale, 1988; DeMarzo and Duffie, 1999). This body of literature typically addresses specific frictions—such as information asymmetry, behavioral biases, non-standard preferences, and agency problems—and explains how securities should be designed to mitigate these issues; see Allen and Barbalau (2024). In contrast, we adopt a broader perspective without taking a stance on a particular underlying friction. Instead, we posit that financial products are characterized by a productivity index that interact with issuer attributes to generate a payoff for investors.

We model firms as having market power when issuing securities. While models of oligopolistic competition in banking are common in the literature (Freixas and Rochet, 1997), and despite recent developments in the study of the industrial organization of financial markets (Clark, Houde and Kastl, 2021), competition between firms when issuing financial products has been understudied. Theoretical work on competition in security markets, from the seminal work of Allen and Gale (1991) to the more recent contribution of Carvajal, Rostek and Weretka (2012), has assumed that the issuers of securities are perfectly competitive and working within complete markets, with a focus on incentives toward introducing new securities.[3] Evidence from Asker and Ljungqvist (2010) shows that firms operating in the same product market are reluctant to share investment banks when issuing securities, suggesting that issuers are concerned about competiting for underwriters. Our model below complements this literature, as a firm's decision to issue a financial product is affected by strategic competition.

Our paper also makes a methodological contribution with its use of model-based decomposition to infer the margins that drive an outcome of interest. For example, Eaton, Kortum and Kramarz (2004), and more recently Hottman, Redding and Weinstein (2016) use the structure of their model to isolate different margins that affect firm sales. To the best of our knowledge, the present paper is the first to apply this methodology to a model of innovation in financial products. These results are relevant to the broader study of the margins that drive innovation. For instance, Garcia-Macia, Hsieh and Klenow (2019) infer sources of growth from patterns in job creation and job destruction data. The present work goes further with direct empirical evidence about the impact of novel financial products.

The rest of the paper is organized as follows. We describe the data we collected in section 2. Section 3 presents stylized facts about financial products and their issuances. Then section 4 outlines our conceptual framework and introduces the model-based decomposition that we use to analyze the data. Section 5 presents the results of our decomposition and highlight

[3] A separate set of papers investigates how the market structure in which financial products are traded affects the design of those financial products (Rostek and Yoon, 2020; Babus and Hachem, 2023).

which mechanisms can explain the variation in proceeds across sectors. We draw conclusions in section 6.

2 Data

We compile granular data to conduct a comprehensive analysis of corporate security issuances. The issuance of a security represents a new contract between a firm (issuer) and investors, which enables the firm to receive funds from investors, and grants investors a claim to a set of cash-flows. We will refer to the type of contract a firm uses as a ”financial product.”

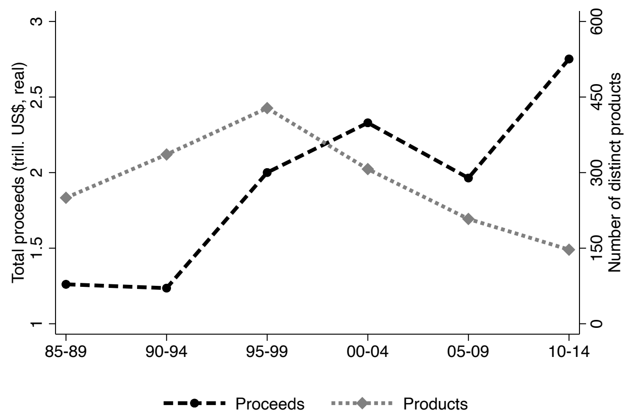
Our main data source is the Global New Issues modules of the Security Database Company Platinum Dataset published by Refinitiv (referred throughout as SDC). The database covers all public, private and Rule-144A issuances of corporate securities with maturities longer than one year (where applicable), excluding derivatives, from 1970 onward. For each issuance of a security we observe the date, the name of the issuing firm, and the type of product issued. Importantly, we also observe the amounts of funds raised, i.e. proceeds, in each issuance. We select issuances originated by any non-financial corporation in the US, and thus exclude from the analysis all issuances where the issuer is part of the government, a federal agency, or a financial institution.[4] We restrict our sample to the period 1985-2014, which allows us to define the year a product is introduced as the year it first appears in the sample. We organize the sample into five-year periods.

The baseline dataset comprises 72,190 issuances by 17,851 issuers, including both publicly listed and private firms, across 847 four-digit SIC sectors. Each firm has, on average, four issuances over the entire period of interest, while the median firm has two. Only 10% of issuing firms have issuances in at least two consecutive periods, which is sparse. Using issuers as our unit of observation would yield variation from only a few (very large) firms. Thus, throughout the paper we use sectors as the unit of analysis to capture heterogeneity across firms and overcome the sparsity of the data.

Firms used 751 types of financial products to raise nearly $11.5 trillion in proceeds over three decades, with substantial heterogeneity in their use across sectors. Table F1 in Appendix F shows that the average sector uses about 14 distinct financial products, while the median uses only 8. Larger sectors — proxied by the number of issuers — tend to issue a

[4]We assess the representativeness of our data by comparing total annual proceeds with those reported in the financial accounts of the United States by the Federal Reserve Board, and we find that the data match almost exactly. See Figure A1 in Appendix A.

Figure 2: Financial Products and Proceeds



Notes: The figure shows the evolution of total proceeds (left axis) and distinct financial products (right axis) from the period 1985-89 to 2010-14. A financial product is counted as active in that period if any firm issued a security of that type in that period.

greater variety of products. These include well-known instruments such as *Common Shares* and *Bonds*, as well as less-familiar financial products like *Equipment Notes*, *Quarterly Income Debt Securities*, and *Senior Pay-In-Kind Notes*. Our differentiation between financial products follows the SDC's categorization of types of securities. Following the SDC categorization when defining a financial product ensures that a change in any attribute of an issuance (e.g. debt instrument, convertibility, the existence and type of collateral, seniority, and maturity) likely results in the SDC registering it as a new type of security.[5]

For each time period, we identify the set of active financial products as those issued by firms during the corresponding quinquennial. Figure 2 shows the evolution of the number of distinct active financial products (right axis) and the proceeds generated through their issuance (left axis) over the period 1985–2014. On average, about 300 distinct products were used over any 5-year period, with a maximum of almost 500 distinct products used in 1995-1999. The proceeds (in real terms) from non-financial corporate issuances in the U.S. show substantial growth over the period 1985-2014. Proceeds represent about \$1.2 trillion in 1985-1989 and \$2.8 trillion in 2010-2014.[6]

Behind these broad patterns, financial products exhibit substantial heterogeneity. Their size distribution follows a strikingly skewed pattern, whether measured in terms of proceeds,

[5]SDC categorizes financial contracts using information from SEC filings, prospectuses, industry news sources, wires, and daily surveys of underwriters and other corporate-finance contacts.

[6]The evolution of proceeds also shows that they seem to have been affected by the global financial crisis, as they increased every quinquennial, with the exception of the quinquennial 2005-2009.

Table 1: Descriptive Statistics of financial products

	Obs	Mean	St.Dev.	P25	P50	P75	P90
Product							
Proceeds	751	15,370	102,573	154	614	2,384	10,408
Issuances	751	96	790	1	4	13	57
Issuers	751	59	540	1	3	10	42
Sectors	751	16	55	1	3	8	31
Duration	621	2.3	1.7	1	2	3	5
Product × period							
Proceeds	1,676	6,887	33,923	117	415	1,562	7,951
Issuances	1,676	43	232	1	3	9	45
Issuer firms	1,676	27	163	1	2	7	29
Issuer sectors	1,676	12	41	1	2	6	22
Product × sector × period							
Proceeds	20,400	566	1,784	47	152	430	1,164
Issuances	20,400	4	11	1	1	3	6
Issuer firms	20,400	2	6	1	1	2	4

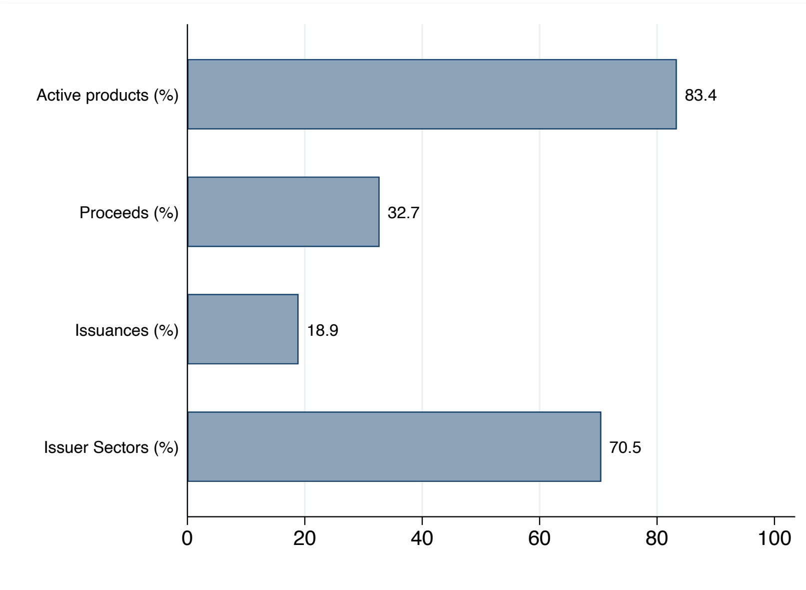
Notes: The table provides various descriptive statistics of the baseline datasets used in the paper: sector, product, product × period, and product × sector × period level. The statistics are computed by pooling data over the period 1985–1989 to 2010–2014. Proceeds are measured in millions US$ (real), while issuances, issuers, sectors (defined by 4-digit SIC codes) and products refer to simple quantities. For each product, we also report duration on the market (total periods active).

number of issuances, or number of issuers. Table 1 presents summary statistics of issuances of financial products over the sample period. We consider different baseline datasets to measure differences across securities. The average financial product was issued by 16 sectors over that period, but the median product was only issued by 3 sectors. Note that the small number of issuers per financial product is prevalent across most products. Even the top 10% most-popular financial products in a sector (i.e., products in the 90th percentile in terms of number of issuers within the sector) are issued by only 9 firms on average.[7]

Also, some products are more long lasting than others. The majority of products are used for only a few periods, and only a few are used frequently. The median product lasts for about two 5-year periods, indicating that some products may be associated with short-lived needs of issuers. For instance, *Extendible Mortgage Bonds* and *Variable Rate Remarketed Bonds* were issued exclusively during the 1985-1990 period. Naturally, some products, such as *Common Shares* and *Global Notes*, are issued in each quinquennial, while some other products like *Mortgage Notes* and *Sinking Fund Debentures* were not issued in recent years.

[7] As an alternative measure of market concentration, we calculate the Herfindahl Index (HHI) for each sector based on financial products between the 25th and 75th percentiles in terms of popularity. Figure E5 in the Appendix E show that the HHI ranges between 0.58 and 1.

Figure 3: Importance of New Financial Products



Notes: The figure shows the relative importance of new financial products, as a proportion of active products, proceeds generated, issuances and issuer sectors over the entire sample period.

3 Key Empirical Facts

In this section, we describe two empirical patterns that motivate our analysis. First, we document substantial variety in the financial products employed by firms over the sample period, driven mainly by the introduction of numerous new instruments. Second, the pattern of financial product usage across sectors shows that most new products are used infrequently, yet play an important role for the firms that adopt them — consistent with these products aligning with firms' specific financing needs or enabling differentiation from competitors.

3.1 The Variety of New Financial Products

The rise in financial product variety is driven by the introduction of numerous new instruments over the three decades covered in our sample. During this period, more than 600 distinct financial products were introduced, representing over 80% of all active products issued by firms between 1985 and 2014, as shown in Figure 3.

We refer to products introduced after 1985 as "new," while those existing before 1985 are labeled "old."[8] New financial products account for one-third of the total proceeds generated

[8]Since our data begins in 1970, we can use the panel structure of the SDC data to determine whether a

by firms over the three decades covered in our sample. Their significance has grown over time, and in the final period, more than 50% of total proceeds were raised through the issuance of new products, as shown in Figure E1 in Appendix E. While they represent only 20% of total issuances, their use is widespread across the majority of sectors. About 40% were first issued privately, with many later becoming publicly traded.

It is important to note that by using SDC's categorization of issuances as the baseline unit of analysis, we do not *ex-ante* distinguish between major and minor differences between financial products. Therefore, we propose a methodology for quantifying the degree of *novelty* of each new financial product relative to existing ones. This will provide insights into whether there is meaningful variety in the types of products issued by firms. We provide a comprehensive description of the procedure in Appendix C.

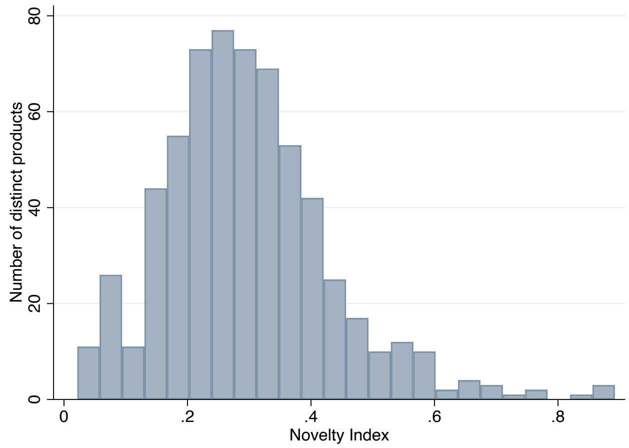
The methodology requires measuring the similarity for each pairs of products. We rely on methods from the literature on natural-language processing for our similarity metric. The baseline algorithm has three steps. First, for each financial products we construct a textual description based on articles from Investopedia.[9] Second, we build a vectorized definition for each financial product (f_i) using relevant information scraped from the article. Vectors of terms result from concatenating all fields into one document, followed by parsing and lemmatizing algorithms. We adjust the weights of each term according to the term-frequency-inverse-document-frequency sublinear transformation and normalize the vectors to unit length. Finally, we construct a dissimilarity score for each pair of products i and j by computing the cosine similarity between the two normalized vectors, $s_{ij} = f_i \times f_j$. This dissimilarity score is defined as $d_{ij} = 1 - s_{ij}$, and takes the value of zero when the two products are perfectly identical. Our algorithm indicates that, for example, the product *Lease Bonds* is similar to *Lease-Backed Certificates*, while the product *Senior Pay-In-Kind Notes* is similar to *Senior Subordinated Pay-In-Kind Notes*, and *Lease Bonds* and *Senior Pay-In-Kind Notes* are quite distinct. For illustration, we provide similarity scores for various pairs of financial products in Table C4 in Appendix C.

The algorithm allows us to quantify the distinction between any two products, and thus provides us with the information we need to build a measure of the degree of novelty of any product relative to prior existing products. The novelty of product i is defined relative to

product issued after 1985 already existed between 1970 and 1985.

[9] We considered several other sources, and Investopedia offers the the most-comprehensive descriptions of securities contracts. We decided not to use alternative multiple sources simultaneously as the measures of similarity would then capture superficial differences in the source material.

Figure 4: Distribution of Novelty of New Financial Products



Notes: The figure presents a histogram of the novelty index for new financial products. Details on the novelty measure are provided in Section 3.1 and Appendix C.

the most-similar product that was created before product i:

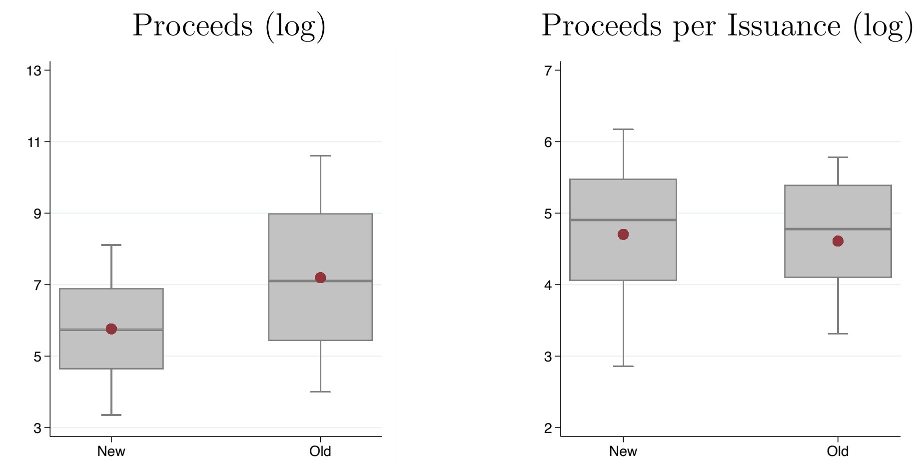
$$N_i = 1 - \max(\Omega_i), \quad \text{where} \quad \Omega_i = \left\{ s_{ij} \cdot \mathbf{1}_{\{c_j < c_i^*\}} \mid j = 1, 2, \ldots, N \right\},$$

cohort c_i is the year in which product i first appeared, and $\mathbf{1}_{\{c_j<c_i*\}}$ is a dummy to indicate that product j was created before product i. This novelty index is guaranteed to be in the range $[0, 1]$, with zero indicating that the product is similar to an existing product, and one indicating that the product is completely distinct from any existing product.

Figure 4 illustrates the distribution of novelty of new financial products. While the average novelty is around 0.25, there is considerable variation. For example, products like *Trust Originated Preferred Securities* and *Quarterly Income Capital Securities* are highly novel, whereas *Convertible Exchangeable Preferred Shares – Series A* and *Floating Rate Asset Backed Certificates* represent relatively minor innovations on existing products. Table C7 in Appendix C provides novelty scores for an illustrative set of financial products. Overall, many new products represent significant departures from existing ones, while even those with lower novelty still introduce distinct variations.

Given these findings, we use two complementary measures to assess the differentiation of financial products: the number of new products and new products weighted by their novelty. These measures enable us to capture innovation in financial products that creates variety in response to market pressures, whether from sudden or gradual changes in the needs of investors or firms raising funds. Throughout the paper, we rely on both measures to evaluate

Figure 5: Distribution of Proceeds, and Proceeds per Issuance



Notes: The figure provides information on the distribution of log proceeds (real terms), and log proceeds per issuance (real terms) for products × period. Statistics for new (introduced after 1985) and old products (introduced before 1985) are provided. For each type of product, we plot five sample statistics - percentile 10, the lower quartile, the median, the upper quartile and the percentile 90 - and the dot indicates the average. We use the baseline data product × period level from period 1985-89 to 2010-14. Figure E4 in Appendix shows the evolution of the average proceeds per issuance. Figure E3 in Appendix shows the distribution of issuances.

the significance of new products in firms' ability to secure external funding.

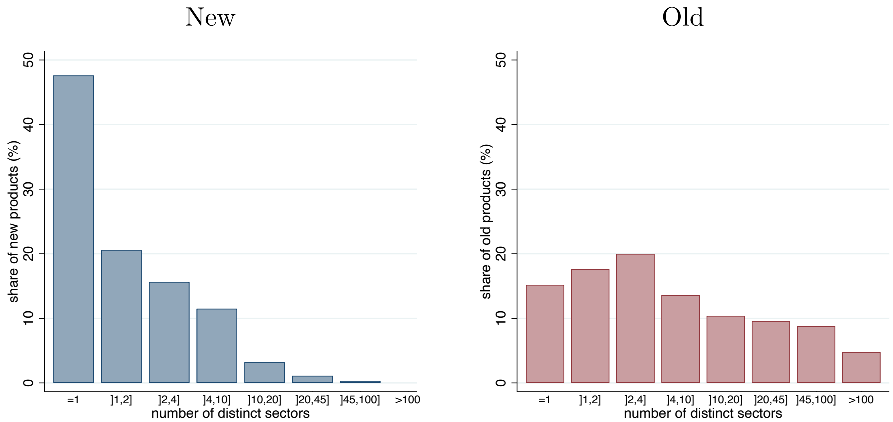
3.2 Sectoral Adoption of New Financial Products

Naturally, firms self-select into the financial products they use, based on their financing needs and market conditions. Therefore, unsurprisingly most new financial products are issued sparingly, which helps explain why, on aggregate, they generate only half the proceeds of old products. Yet, their adoption patterns suggest they play a significant role for the firms that use them, as we document below.

We start by comparing the distribution of new and old products, in terms of total proceeds. On average, each new product generates less proceeds than old products. Indeed, the distribution of (log) proceeds of new products is centered around lower values than the distribution of the (log) proceeds of old products (Figure 5, left plot). Yet, both the median old product and the median new product generate nearly \$150 million in proceeds per issuance, although new products exhibit greater dispersion (Figure 5, right plot). For reference, *Common Shares* generate on average \$93.5 million per issuance, which corresponds to the 39 percentile. This indicates that firms issuing new financial products raise amounts of proceeds comparable to those raised by issuing old products.

The difference between the distribution of products based on total proceeds and proceeds

Figure 6: Distribution of Financial Products Among Issuer Sectors



Notes: The left figure divides new financial products by the numbers of issuer sectors that used them in a period. The figure on the right shows the equivalent statistics for old products. We use data at the baseline product × period level and compute how many distinct sectors use that product in that time period, we then average across periods where that product was active.

per issuance is explained by the fact that new products are issued less frequently than old products. Indeed, the product in the 90th percentile of issuances is only slightly higher than the median old product (see Figure E3 in Appendix E).

We next examine distribution of new and old products, based on the number of distinct sectors issuing each product. Figure 6 shows striking differences sectoral adoption between new and old products. Notably, about half of new products are only used by one sector in any period, compared to only 15% for old products. For instance, *Secure Principal Energy Receipts* is issued by two firms in the sector *Crude Petrol, Natural Gas*, while *PERLS* is issued by one firm in the sector *Electrical Equipment*. Table 2 provides several additional examples of new financial products from the left tail of the distribution, along with their corresponding issuer sectors. Conversely, nearly 15% of old products are used in more than 20 sectors in any particular period, while less than 2% of new products are used in more than 20 sectors (e.g. products like *Asset Backed Certificates* and *Senior Unsecured Notes*). This pattern suggests that most new products are specialized, while older products are more generic and broadly applicable.

To further understand the patterns of sectoral adoption, we divide financial products into quintiles based on the number of sectors using each one. The products listed in Table 3 are examples from the bottom quintiles, whereas *Common Shares* falls into the top quintile. A product in the first quintile (highly specialized) is, on average, used by only one sector,

Table 2: Examples of Products and Issuer Sectors

Product	Sector	Issuers	Issuances	Proceeds per Issuance
Auction Market Preferred Stock	Electric Services	3	4	68.7
Auction Market Preferred Stock	Engineering Services	1	1	409.7
Auction Rate Debentures	Telephone Communication	1	1	183.0
Equipment Trust Notes	Air Transportation	1	4	28.3
Equipment Trust Notes	Equip. Rental, Leasing	1	2	261.5
Equipment Trust Notes	Railroads	2	14	16.7
Premium Income Equity Securities	Amusement Parks	1	1	281.0
Premium Income Equity Securities	Cable and Television	2	2	1,688.3
Premium Income Equity Securities	Department Stores	1	1	103.5
Premium Income Equity Securities	Electric and Related	1	1	267.2
Premium Income Equity Securities	Electric Services	2	2	233.7
Principal Exchange Rate Linked Sec.	Electrical Equipment	1	1	67.5
Secure Principal Energy Receipts	Crude Petrol, Natural Gas	2	3	93.3
Struct. Asset Trust Unit Repackaging	Motor Vehicles	5	5	50.7

Notes: The table presents several examples of financial products issued by only a few sectors, along with the corresponding issuing sector. For each product, it reports the number of issuances and issuers within that sector, as well as the average proceeds per issuance.

whereas a product in the fifth quintile (widely adopted) is used by approximately 70 sectors. Even products in the middle quintile are, on average, used by only three sectors, indicating that many products are fairly specialized.

The vast majority of products in the first quintile—nearly 95%—are new, compared to just over half in the fifth quintile. Average proceeds per product are significantly smaller in the first quintile than in the fifth, which is consistent with Figure 5. However, despite being issued only twice on average, products in the first quintile generate higher proceeds per issuance than those in the fifth, suggesting that specialized products may be matched to the right issuers.

The use of specialized financial products is notably tilted toward large sectors. Nearly 70% of products in the first quintile—those used by the fewest sectors—are adopted by large sectors, defined as those in the 90th percentile of proceeds raised. In contrast, while products in the fifth quintile — such as *Common Shares* — are issued across virtually all sectors, only 50% of them are used by large sectors. At the same time, even highly specialized products from the first quintile are employed by over 100 sectors, suggesting that these products are horizontally differentiated.

Additional evidence of horizontal differentiation comes from comparing the proceeds-based ranking of financial products across sectors. In the absence of such differentiation, if a given set of products is available in two sectors, their relative rankings should be similar. To

Table 3: Financial Products across Quintiles of Number of Issuer Sectors

	1	2	3	4	5
Characteristics quintiles					
Number of products	256	109	105	135	146
Average number of sectors	1.0	2.0	3.4	6.9	71.8
New versus Old					
Share new products	0.94	0.90	0.87	0.85	0.56
Size of products					
Average proceeds	385	639	1,034	2,815	74,561
Average issuances	1.9	4.2	6.4	12.3	471.6
Average proceeds per issuance	260.9	199.4	188.7	237.1	196.1
Average number of issuer firms	1.1	2.5	4.1	8.1	237
Duration					
Average duration	1.1	1.1	1.45	1.68	3.35
Share of single issuance	0.75	-	-	-	-
Issuer Sectors					
Total number of distinct sectors	128	121	148	295	842
Share large sector %	0.68	0.64	0.68	0.63	0.50

Notes: The table provides various descriptive statistics of the financial products organized into the quintiles of number of issuers sectors (defined by 4-digit SIC codes) using the products. The statistics are computed by pooling data over the period 1985–1989 to 2010–2014. Proceeds are measured in millions US$ (real), while issuances and, issuers, sectors (defined by 4-digit SIC codes) refer to simple quantities. For each product, we also report duration on the market (total years active).

examine this, we compute product ranks by proceeds for each sector and time period, and then calculate the average rank correlation across all sector pairs. The resulting correlation is 0.37. When we restrict the comparison to products with positive proceeds in both sectors, the average correlation drops to 0.03. [10] Figure E6 in Appendix E presents both measures over time. Both rank correlations are small, supporting the view that financial products are horizontally differentiated.

Taken together, these results indicate that new financial products contribute to overall proceeds through a large number of distinct instruments that, while not widely adopted, generate significant funding for the firms that use them.

[10] The unrestricted rank correlation may be affected by products that return zero proceeds. However, products might have zero proceeds because they are unavailable in some sectors. Since we cannot identify the reason that a product issued in a sector but not in another, we provide the alternative restricted exercise.

4 Conceptual Framework

In this section we propose a parsimonious model of security issuance. Our main focus is on firms' decisions to issue financial products, which are then acquired and traded by investors. To account for the large variety of financial products observed in the data, we distinguish financial products based on a productivity index which interacts with sector- and firm-specific risk factors to yield a payoff to investors. Similarly to Callander, Lambert and Matouschek (2022), financial products are both horizontally differentiated (across sectors) and vertically differentiated (within sector).

We consider two motives for firms when issuing securities. On the one hand, firms favor products with high-productivity because investors value them and they can generate higher proceeds. On the other hand, firms may choose to issue products so they can differentiate themselves from competitors. To this end, the model implements a market structure where firms operate in an oligopoly, issuing differentiated financial products, while investors take prices as given.[11]

The model implies that multiple products with varying productivity are issued in equilibrium, with many being issued only sparingly. We use this framework to develop a structural decomposition to estimate how financial product productivity contributes to variation in firms' success in raising funds. This decomposition allows us to empirically analyze the role of specialized products without structuring the model to favor specialization. All proofs relevant to this section are collected in Appendix D.

4.1 Issuers and Financial Products

The model economy has one period and a finite set of firms distributed across S sectors. Each sector $s \in S$ is populated by L_s firms. In each sector s there exists a set $\mathcal{I}_s$ of financial products that firms can choose to issue in order to raise funds from investors.[12] A financial product is a contract that specifies a set of payoffs for investors as a function of the issuer's attributes, such as projects she undertakes, her ability to manage those projects, as well as overall riskiness. Firms within the same sector share common attributes, and we allow for the possibility that some financial products may be a better match for issuers in some sectors than they are for issuers in other sectors.

[11] These conditions of imperfect competition between firms are consistent with the patterns in Section 3.2.

[12] We take as given that multiple financial products are potentially available in a sector, relying on an extensive literature that microfounds departures from the Modigliani and Miller result. See Allen and Barbalau (2024) for a recent survey.

A firm $\ell \in L_s$ in sector s chooses one type of financial product $i \in \mathcal{I}_s$ that she can issue at the beginning of the period. A financial product i represents a vector of characteristics $\mathbf{c_i}$ that maps a issuer ℓ risk-factors, captured by a random variable θ_ℓ, into a set of of stochastic payoffs $W_{i\ell}$ to be paid by the firm to investors at the end of the period. We assume that the mapping is linear such that when firm ℓ issues financial product i, then the resulting claim $W_{i\ell}$ is

$$W_{i\ell} = x_{is}(\mathbf{c_i}) + z_{is}(\mathbf{c_i})\theta_\ell. \tag{1}$$

The functions $x_{is}(\mathbf{c_i})$ and $z_{is}(\mathbf{c_i})$ describe how the characteristics of product i affect the payoff that investors receive for each realization of θ_ℓ. Note that specification (1) introduces the distinction between a financial product which is a technology that can used by many firms, and a financial claim which represents a set of state-contingent payoffs issued by a particular firm.

Specification (1) provides a parsimonious representation of financial products. Each product is exhaustively described in terms of how it affects the expected payoff and the risk for investors. As a result, each financial product i issued by firms in sector s can be identified by an index χ_{is}, defined as follows:

$$\chi_{is} \equiv \frac{x_{is}(\mathbf{c_i})}{z_{is}(\mathbf{c_i})}. \tag{2}$$

We refer to χ_{is} as the productivity of the match between financial product i and issuers in sector s. The productivity of a financial product i maps directly into the Sharpe ratio of a financial claim $W_{i\ell}$. A product with a higher sector-specific productivity χ_{is} implies that the claim $W_{i\ell}$ provides investors a higher expected value per unit of risk for any issuer ℓ in sector s. Thus, for investors with mean-variance preferences, a product with a higher productivity improves their expected utility from holding claims of firms that issue the product.

Under our representation, products i and j with different set of characteristics would yield a different set of payoffs for investors even if they were to be issued by the same firm ℓ. For instance, under one interpretation, a product with a collateralization characteristic reduces the risk of the claim that firm issues for investors relative to a product that lacks such a characteristic. At the same time, the characteristics, $\mathbf{c_i}$, of a financial product i can result in a different set of payoff for investors depending on the sector of the issuer. For instance, products that require collateral may be a better match for firms in sectors with a lot of physical assets than those that rely heavily on intangible assets. Thus financial products are horizontally differentiated across sectors.

The riskiness, θ_ℓ, of issuer ℓ in sector s is composed of a common component for all firms in the sector, θ_s, and an idiosyncratic component specific to the firm, ε_ℓ, as follows

$$\theta_\ell = \theta_s + \varepsilon_\ell.$$

We assume that $E(\theta_s) = E(\varepsilon_\ell) = 0$, so that that the expected payoff of a claim $W_{i\ell}$ is $E(W_{i\ell}) = x_{is}$. Let the variance $\mathcal{V}(\theta_s) = \sigma_s^2$ differ across sectors, while $\mathcal{V}(\varepsilon_\ell) = \sigma_{\varepsilon_s}$ is the same for all firms $\ell \in L_s$. At the same time $cov(\varepsilon_\ell, \varepsilon_{\ell'}) = 0$ for any ℓ, ℓ'. For the sake of tractability, we assume that $cov(\theta_s, \theta_{s'}) = 0$, so that $cov(\theta_\ell, \theta_{\ell'}) = 0$ for any $\ell \in L_s$ and $\ell' \in L_{s'}$ for any two sectors s and s'.

Specification (1) implies that investors receive different, albeit correlated, payoffs from the same financial product, if the product was issued by two different issuers ℓ and ℓ' in sector s. In particular, the correlation between any two claims $W_{i\ell}$ and $W_{i\ell'}$ issued by firms ℓ and ℓ' in the same sector s is given by

$$\rho_s \equiv Corr(W_{i\ell}, W_{i\ell'}) = \frac{\sigma_s^2}{\sigma_s^2 + \sigma_{\varepsilon_s}^2}.$$

Firms' choices of which financial product to issue determine a distribution of issuers across products. Let L_{is} be the set (and number) of firms in sector s that issue financial product i, so that $L_s = \bigcup_{i \in \mathcal{I}_s} L_{is}$ and $L_{is} \cap L_{i's} = \emptyset$. We allow for the possibility that there exist financial products $i \in \mathcal{I}_s$ so that $L_{is} = \emptyset$.

After choosing which financial product $i \in \mathcal{I}_s$ to issue, each firm $\ell \in L_s$ chooses the quantity $a_{i\ell}$ of the claim $W_{i\ell}$ to supply to investors in order to maximize the expected net revenue from the issuance:

$$V_\ell(a_{i\ell}) = E(p_{i\ell} - W_{i\ell}) \times a_{i\ell}, \tag{3}$$

where $p_{i\ell}$ represents the market price determined when investors trade the claim $W_{i\ell}$. The issuer's expected payoff in (3) aligns with the specification in many other studies that follow DeMarzo and Duffie (1999), where the issuer offers a single security backed by a project, albeit we abstract from asymmetric information considerations.[13]

[13] We implicitly assume that firm ℓ invests the proceeds $p_{i\ell}a_{i\ell}$ in a project which returns in expectation one dollar per dollar invested, and that the firm has deep pockets and can use other assets to pay the payoff $W_{i\ell}$ to investors, so no default occurs. The model implications are robust to assuming that the project has an expected return larger than one.

4.2 Investor Demand

We intentionally adopt a standard approach to modeling investors, as our main focus is on firms' decisions to issue financial products. While many factors can influence investor demand, our model assumes that risk diversification is the primary driving force. Specifically, the demand for securities arises from a continuum of investors that are segmented over financial products. Investors segmentation is prevalent in financial markets (Wittwer and Uthemann, 2025). This is either because investors face regulatory constraints that restrict which products they can hold, or because investors need to exert time and effort to evaluate and acquire information about complex products (Van Nieuwerburgh and Veldkamp, 2010). Such frictions ultimately imply additional costs that investors incur when holding a portfolio that consists of multiple financial products. For tractability, to derive an inverse demand function for financial claims, we consider that the costs of holding multiple products are prohibitive, so that an investor n can acquire only one type of financial product $i \in I_s$. However, investor n can trade all claims issued by firms $\ell \in L_{is}$ in any sector $s \in S$. Let η_s be the mass of investors that acquire each financial product i in sector s.

In a typical CAPM economy, investor demand for financial products is shaped by a mean-variance trade-off. Accordingly, we assume that each investor n's preferences are given by

$$U^n = \zeta^n E\left(C^n\right) - \frac{\gamma}{2}\mathcal{V}\left(C^n\right) - \sum_{s\in S_n}\sum_{\ell\in L_{is}} p_{i\ell}q_{i\ell}^n \tag{4}$$

where $q_{i\ell}^n$ is the quantity of the claim $W_{i\ell}$ held by the investor, and C^n is the total consumption determined as $C^n = \sum_{s\in S_n}\sum_{\ell\in L_{is}} q_{i\ell}^n W_{i\ell}$. The term ζ_n is an idiosyncratic preference shock with mean μ_ζ that shifts the investor's marginal utility of consumption, following Rostek and Weretka (2012) and Vives (2011). Essentially, ζ_n introduces a layer of heterogeneity across investors at the moment of trading.[14]

Investors in financial product i can choose which claims $\{W_{i\ell}\}_{\ell\in L_{is}}$ they want to trade, managing their holdings in order to maximize utility (4). Since claims have partially correlated payoffs and investors dislike risk, the optimal choice is to diversify and hold a position in each claim. The following lemma characterizes the inverse demand that arises in equilibrium for each claim $W_{i\ell}$.

[14] E and $\mathcal{V}$ are the expected-value and variance operators.

Lemma 1 *The inverse demand for claim $W_{i\ell}$ issued by firm ℓ in sector s is given by*

$$p_{i\ell}\left(a_{i\ell}\right)=\mu_{\zeta}E\left(W_{i\ell}\right)-\frac{\gamma}{\eta_s}z_{is}^2\left(\sigma_s^2+\sigma_{\varepsilon_s}^2\right)\left(\left(1-\rho_s\right)a_{i\ell}+\rho_s\sum_{\ell'\in L_{is}}a_{i\ell'}\right)\qquad(5)$$

Lemma 1 implies that issuer ℓ faces an inelastic demand from investors. Because investors can diversify across financial claims, the inverse demand for $W_{i\ell}$ decreases not only with the quantity $a_{i\ell}$ that firm ℓ supplies, but also with the aggregate supply $\sum_{\ell'\in L_{is}}a_{i\ell'}$ provided by all firms issuing product i. The stronger the correlation ρ_s is, the less investors can diversify between any two claims $W_{i\ell}$ and $W_{i\ell'}$, and the higher the elasticity of demand is. Conversely, when the correlation ρ_s is weak and claims provide more diversification benefits, the demand is more inelastic.

4.3 The Equilibrium Allocation of Financial Products

In this section, we analyze firms' decisions on which financial product to issue and how much to supply to the market. When choosing the quantity $a_{i\ell}$ of product i to issue, firm ℓ faces inverse demand (5) and must account for the quantity, $a_{i\ell'}$, that the other competing firms $\ell'\in L_{is}$ are issuing. Similarly, when firm ℓ chooses financial product i, she takes as given the choices of other firms $\ell'\in L_s$ in sector s. The following definition formalizes this notion of equilibrium.

Definition 1 *Equilibrium in sector s is a distribution of issuers across products $\{L_{is}\}_{i\in\mathcal{I}_s}$ and a set $I_s\subseteq\mathcal{I}_s$ of issued financial products, as well as quantities $\{a_{i\ell}^*\}_{i\in I_s,\ell\in L_{is}}$ such that*

1. *For each issuer ℓ that chooses product i with L_{is} issuers, $a_{i\ell}^*$ solves problem*

$$\max_{a_{i\ell}}\left\{E\left(p_{i\ell}-W_{i\ell}\right)\times a_{i\ell}\right\}$$

given the inverse demand $p_{i\ell}$ in Equation (5);

2. *no issuer ℓ of product i benefits from deviating and switching to another product i', i.e., the payoff that ℓ receives from deviating and issuing product i' with $L_{i's}$ issuers is less than the payoff ℓ receives from issuing product i with L_{is} issuers, for any $i'\neq i$*

$$V_{\ell}\left(a_{i\ell}^*\right)\geq V_{\ell}\left(a_{i'\ell}^*\right).$$

Given a set of products issued in by firms in sector s and a distribution of issuers among products, the first-order condition for a firm ℓ that chooses to issue quantity $a_{i\ell}$ of product i is

$$E\left(p_{i\ell} - W_{i\ell}\right) + \frac{\partial p_{i\ell}}{\partial a_{i\ell}} \times a_{i\ell} = 0 \tag{6}$$

where $p_{i\ell}$ represents the inverse demand in Equation (5). The first term in Equation (6) represents the marginal benefit that firm ℓ obtains by supplying an additional unit of claim $W_{i\ell}$ to investors. However, increasing the quantity supplied imposes an indirect cost as the price of claim $W_{i\ell}$ depends on firm ℓ's choice - a cost captured by the second term in Equation (6). To track firm ℓ's the ability to influence the price we use a standard measure of market power, namely the ratio of price minus marginal cost to price, or the Lerner index defined in our setup as

$$\Lambda_{i\ell} = \frac{E(p_{i\ell} - W_{i\ell})}{E(p_{i\ell})}. \tag{7}$$

The Lerner index ranges between 0 and 1, with lower values indicating that firm ℓ has more competition. An issuer faces competition from other firms issuing the same product, as their financial claims are correlated. When the payoffs of two claims $W_{i\ell}$ and $W_{i\ell'}$ are correlated, investors can partially substitute between them in their portfolios. For instance, if the price of claim $W_{i\ell'}$ decreases, an investor may find it beneficial to buy more of $W_{i\ell'}$ and less of $W_{i\ell}$, *ceteris paribus*. Thus, when issuer ℓ supplies a larger quantity $a_{i\ell}$ of the claim $W_{i\ell}$, the price $p_{i\ell}$ decreases as a direct effect, and the price $p_{i\ell'}$ also decreases, as an indirect effect. The following proposition characterizes the equilibrium quantity that each firm ℓ issuing product i supplies,

Proposition 1 *Given a set of financial products I_s that are issued in sector s and a distribution of firms across products $\{L_{is}\}_{i \in I_s}$, the optimal quantity that firm ℓ in sector s issues of product i is*

$$a_{i\ell}^{*} = \frac{x_{is}}{z_{is}^{2}} \frac{1}{\left(\sigma_s^2 + \sigma_{\varepsilon_s}^2\right)} \frac{\Lambda_{is}}{1 - \Lambda_{is}} \frac{\eta_s}{\gamma}, \tag{8}$$

and

$$\Lambda_{i\ell} \equiv \Lambda_{is} = \frac{\left(\mu_\zeta - 1\right)}{\left(L_{is} - 1\right)\rho_s + \mu_\zeta + 1} \tag{9}$$

for any $\ell \in L_{is}$.

As expected, a firm $\ell \in L_{is}$ issues a greater quantity of the claim $W_{i\ell}$ if the product i maps into a claim with higher expected value (high x_{is}) or lower variance (low z_{is}). The firm also issues a greater quantity when facing stronger investor demand, which is represented by a larger set of investors η_s or a lower risk aversion γ. Conversely, in sectors with more risk, measured by either sectoral volatility, σ_s^2, or idiosyncratic firm volatility, $\sigma_{\varepsilon_s}^2$, the firm issues less, all else equal. Moreover, as more firms choose to issue product i, firm ℓ issues less of her claim. This relationship is a direct effect of investors' ability to substitute between financial claims, which introduces imperfect competition between issuers.

These forces anticipate the trade-offs that firms face when choosing which financial products to issue. Issuing a greater quantity is desirable for firm ℓ, as the first-order condition (6) implies that the expected payoff to firm ℓ is given by

$$V_\ell\left(a_{i\ell}\right) = z_{is}^2\left(\sigma_s^2 + \sigma_{\varepsilon_s}^2\right)\left(a_{i\ell}\right)^2 \frac{\gamma}{\eta_s},$$

or, substituting the quantity $a_{i\ell}$ from Equation (8),

$$V_\ell\left(a_{i\ell}\right) = \frac{\chi_{is}^2}{\sigma_s^2 + \sigma_{\varepsilon_s}^2}\left(\frac{\Lambda_{is}}{1-\Lambda_{is}}\right)^2 \frac{\eta_s}{\gamma}, \tag{10}$$

where χ_{is} was defined in Equation (2) as the productivity of the financial product i. Note that the ratio $\frac{\chi_{is}}{\sqrt{\sigma_s^2+\sigma_{\varepsilon_s}^2}}$ represents the Sharpe ratio of claim $W_{i\ell}$. Claims with higher Sharpe ratios increase issuers' expected payoffs, leading firms to favor financial products with higher productivity. At the same time, firms prefer products with limited competition, which allow them to benefit from a thin supply. The tension between the productivity of a product and a firm's need to differentiate from competitors shapes the equilibrium distribution of issuers across products. The following proposition formalizes this reasoning.

Proposition 2 *A distribution of issuers across products in sector s, $\{L_{is}\}_{i\in\mathcal{I}_s}$, is supported in equilibrium if*

$$\chi_{is}\frac{\Lambda_{is}}{(1-\Lambda_{is})} = \chi_{i's}\frac{\Lambda_{i's}}{(1-\Lambda_{i's})}, \tag{11}$$

for any $i, i' \in \mathcal{I}_s$. The set of financial products issued in equilibrium by firms in sector s is $I_s = \{i|\ s.t.\ L_{is} \geq 1\}$.

If condition (11) holds, then an issuer ℓ of product i with L_{is} issuers would not want to deviate and issue product i' with $L_{i's}$ issuers. Firm ℓ understands that if she deviates and issues product i', she will face $L_{i's}$ other issuers, while if she issues product i she will face $(L_{is}-1)$ other issuers. Condition (11) ensures that the payoff that firm ℓ expects when she issues product i is at least as large as the payoff she would obtain in expectation if she deviates and issues product i'. At the same time, condition (11) also ensures that the issuer

ℓ' of product i' with $L_{i's}$ issuers would not want to deviate and issue product i with L_{is} issuers. For the remainder of our analysis we focus on equilibria that are supported under condition (11).

The set of financial products issued in equilibrium depends on the products available to a sector and its size (proxied by the number of issuers), meaning that not all available products in sector s must be issued. To see this, consider the special case in which only two products are available to sector s, so that $\mathcal{I}_s = \{i, i'\}$, with productivity $\chi_{is} > \chi_{i's}$. If the difference in productivity between the two products is so large that

$$\frac{\chi_{is}}{\chi_{i's}} > 1 + \frac{\rho_s}{2}(L_s - 1),$$

it can be shown that the payoff that a firm expects when issuing product i is higher than the payoff she expects when issuing product i', even when the firm is the only issuer of product i'. In this case, only the highest-productivity product is issued in equilibrium. However, if the productivity difference between the two products is sufficiently small or if the sector has many issuers, both products are issued. This example suggests that products of productivity below a sector-specific threshold are sufficiently unappealing to firms that none are issued in equilibrium. Furthermore, a higher-productivity product in a given sector is more appealing to and attracts more issuers than a lower-productivity product. The following corollary formalizes these two implications.

Corollary 1 *Consider the set $I_s = \{i| \text{ s.t. } L_{is} \geq 1\}$ of financial products issued in equilibrium by firms in sector s.*

1. *The lowest-productivity product, $\chi_{is}^{\min}$, that is issued in equilibrium in sector s satisfies the following condition*
$$\chi_{is}^{\min} \geq \frac{1}{1 + \frac{\rho_s}{2}(\frac{L_s}{I_s} - 1)} \frac{\sum_{i \in I_s} \chi_{is}}{I_s}. \tag{12}$$
2. *For any two products i and $i' \in I_s$ such that $L_{is} \leq L_{i's}$, it must be that $\chi_{is} < \chi_{i's}$. The equilibrium proceeds associated with product i' are also larger than proceeds associated with product i.*

It is worth emphasizing the role that the imperfect competition between firms plays in shaping the equilibrium distribution of issuers across products. To understand the implications of a firms' strategic behavior, we consider a scenario in which firms take the price of the financial product they supply to investors as given. In other words, let $\frac{\partial p_{i\ell}}{\partial a_{i\ell}} = 0$ in the first-order condition (6) for any firm ℓ and product i. It immediately follows that firms' profits described in Equation (3) are equal to zero. In this case, firms are indifferent about which products to issue, and a distribution of issuers across products in which all firms issue the highest-productivity product in a given sector can be supported in equilibrium. Thus, the imperfect competition between issuers pushes firms down the productivity ladder, and this structural force means that products of varying productivity are issued in equilibrium.

4.4 From Model to the Data

The model provides a framework that captures key factors influencing firms' success in obtaining financing through security issuance. In this section, we use the model to develop an empirical strategy for quantifying how different sources of sector heterogeneity contribute to the variation in firms' ability to raise external funding. We focus on the role of product varieties available to firms within a sector.

4.4.1 Model-based Decomposition

Firms' ability to raise external financing can be quantified by the total proceeds in each sector s, which depends on the set of products issued in equilibrium, the size of the sector, proxied by the number of issuers in the sector, issuers' risk factors, and the demand from investors.

We derive the total proceeds obtained by issuers in a given sector by first obtaining the expected proceeds of firm ℓ in sector s that issues product i in equilibrium, $E\left(p_{i\ell}\right) \times a_{i\ell}$, by substituting the optimal quantity, $a_{i\ell}$, issued by each firm ℓ, as described by (8), into the price (5) which yields

$$E\left(p_{i\ell}\right) \times a_{i\ell} = \chi_{is}^2 \frac{1}{\left(\sigma_s^2 + \sigma_{\varepsilon_s}^2\right)} \frac{\Lambda_{is}}{\left(1-\Lambda_{is}\right)^2} \frac{\eta_s}{\gamma}.$$

Then we employ condition (11) and obtain the total proceeds generated in sector s by aggregating across all firms and all products issued in equilibrium. We show that log proceeds in sector s can be decomposed broadly into three additive and separable components:

$$\begin{aligned}
\log Y_s = {} & 2\log\left[\frac{\sum\limits_{i\in I_s}\chi_{is}}{I_s}\right] && \text{Average productivity} \\
& + \log\frac{\sum\limits_{i\in I_s}\frac{\omega_{is}}{L_{is}}\Lambda_{is}}{\frac{1}{I_s}\left[\sum\limits_{i\in I_s}\frac{\omega_{is}}{L_{is}}\left(1-\Lambda_{is}\right)\right]^2} + \log\frac{1}{\left(\sigma_s^2+\sigma_{\varepsilon_s}^2\right)} && \text{Competition \& Risk} \\
& + \log\left[\frac{\eta_s}{\gamma}\right] && \text{Demand,} \qquad (13)
\end{aligned}$$

where ω_{is} represents the share of total proceeds in sector s attributed to product i. The derivations are provided in Appendix D.

Dispersion in proceeds across sectors arises in response to various forces. One of the primary drivers of sector heterogeneity, as seen through the model, is the differential adoption of financial products across sectors. Firms in different sectors issue different sets of products because sector size (i.e., the number of issuers) varies and because they face different distributions of product productivity. Indeed, in larger sectors, more products satisfy the cutoff for productivity $\chi_{st}^{\min}$ defined in Equation (12). Thus, if products had the same productivity in all sectors, the average productivity of products issued in larger sectors would be lower. However, this effect is offset as a greater variety of products in sector s not only opens more markets for firms but also reduces competition within any single product, enabling issuers to raise more funds overall.

Naturally, the model allows that issuers in different sectors face different distributions of product productivity. Even if two sectors, s and s', are of the same size (proxied by the number of issuers), the allocation of issuers across financial products may still differ. Consequently, the set of products issued in equilibrium in sector s may have a higher average productivity than in sector s', which in turn leads to larger proceeds in sector s , as implied by Equation (13). This occurs because firms issue larger quantities of higher-productivity products, as shown in Proposition 1.

Besides access to financial products, both demand and supply factors shift proceeds. Proceeds are clearly larger when a sector faces stronger demand, proxied either through a higher η_s or μ_ζ, or lower γ. On the supply side, differences in riskiness across sectors and firms affect proceeds. *Ceteris paribus*, sectors with greater uncertainty generate lower proceeds. The *ceteris paribus* assumption includes keeping the set of products issued in equilibrium remains the same. Note, however, that condition (11) implies that both the set of products and the quantities issued in equilibrium in sector s depend on risk at the levels of both firms and sectors.

4.4.2 Empirical Strategy

The decomposition of total proceeds in sector s provided in Equation (13) reflects multiple sources of heterogeneity across sectors and depends on both observable and unobservable variables. While for each period t in our sample we observe the number of distinct issuers L_{ist}, the proceeds weights ω_{ist}, and the set of distinct products I_{st}, certain key components remain unobservable. Specifically, given a set of parameters $\{\mu_\zeta, \gamma, \sigma_{st}, \sigma_{\varepsilon_{st}}\}$, we cannot directly observe the productivity of the financial products χ_{ist}, and the mass of investors η_{st}.

Note that by combining the first term (average productivity) and the third term (risk) in Equation (13), we obtain the average Sharpe ratio of financial claims issued in sector s. However, while Sharpe ratios are readily available for publicly traded claims, no equivalent measure exists for privately issued claims. As a result, we still face the challenge of unobservable productivity.

The difficulty of measuring productivity with limited data is generally pervasive in fields like macroeconomics and industrial organization. Our empirical strategy for implementing the decomposition consists in addressing the fact that the mass of investors is unobserved, and inferring the productivity of product types without taking a stance on an actual value. To this end, we consider that the decomposition in Equation (13) holds in every period t. Moreover, we assume that the evolution of the mass of investors across sectors satisfies the following assumption.

Assumption 1 *The evolution of the mass of investors working with a sector satisfies* $\log \eta_{st} = \log \eta_s + \log \psi_t$

Under this assumption, we then show that we can separate the role that demand plays in the evolution of proceeds across sectors over time. We evaluate the adequacy of Assumption 1 by using external proxies for the evolution of the mass of investors across sectors in Section 5.1.

Proposition 3 *If Assumption 1 holds, changes in (log) proceeds will be:*

$$\Delta^{s,t}\log(Y_{st}) = \underbrace{\Delta^{s,t}2\log\left[\frac{\sum_{i\in I_{st}}\chi_{ist}}{I_{st}}\right]}_{\Delta^{s,t}\bar{\chi}_{st}} + \underbrace{\Delta^{s,t}\left[\log\frac{\sum_{i\in I_{st}}\frac{\omega_{ist}}{L_{ist}}\Lambda_{ist}}{\left[\sum_{i\in I_{st}}\frac{\omega_{ist}}{L_{ist}}\left(1-\Lambda_{ist}\right)\right]^2} + \log\frac{1}{\left(\sigma^2_{st}+\sigma^2_{\varepsilon_{st}}\right)}\right]}_{\Delta^{s,t}Z_{st}}$$

where $\Delta^{s,t}$ stands for the double difference operator for sector s over time t of log proceeds, log average productivity, and the component capturing competition and risk, respectively.

The proof is provided in Appendix B.

The main implication of Proposition 3 is that we can infer the double difference in average product productivity, $\Delta^{s,t}\bar{\chi_{st}}$, from the difference between $\Delta^{s,t}\log\left(Y_{st}\right)$ and the double difference of the competition and risk component, $\Delta^{s,t}Z_{st}$. To see this, it is useful to recall that we observe the number of issuers L_{ist} and the set of products I_{st}, and it is straightforward to calculate the share of proceeds, ω_{ist}, associated with product i. Given a set of estimated parameters, we can then impute the Lerner index, Λ_{is}, based on Equation (9), and obtain $\Delta^{s,t}Z_{st}$.

Because our measure of productivity represents variation in the proceeds growth rate that cannot be explained by observable variables, it is essentially a residual. This is typical in many studies that conceptualize productivity metrics as a ratio of outputs to inputs. For example, empirical work in the industrial organization literature refers to any demand shifter conditional on price as "productivity", and several methods to measure this construct have been developed (see De Loecker and Syverson (2021) for a survey). While our model captures several relevant forces that influence firms' issuance strategies, such as competitive forces and issuer-specific risk factors, our productivity measure can end up embodying sources of proceeds variation, such as firms' connections to underwriters or underwriters' ability to place securities, that are conceptually distinct from security design. For this reason, in Section 5.2 and 5.3 below we aim to shed light on the nature of productivity.

5 Results

Guided by the model, we study the impact of the adoption of an increasingly specialized variety of financial products on a firms' ability to raise external funds. First, we estimate the components of the model-based decomposition and evaluate the importance of the component capturing changes in the average productivity of financial products. Second, we show that the innovations represented by new financial products are associated with increases in the average productivity component. Finally, we evaluate how the substantial heterogeneity in the adoption of new financial products across firms is also more strongly associated with increases in the average productivity component.

5.1 Decomposition and Average Productivity

Estimation of parameters – To implement the decomposition described in Proposition 3 we first need to estimate the demand parameter, μ_ζ, and the parameters associated with differences in risk across sectors, $\{\sigma_{\varepsilon_{st}}, \sigma_{st}\}$. The demand parameter μ_ζ captures on average the taste of investors for holding any financial product. Our approach is to calibrate μ_ζ to 2, and test robustness for alternative values.

To obtain measures of sector risk, σ^2_{st}, and firm-specific risk, $\sigma^2_{\varepsilon_{st}}$, we use annual firm-level data from Compustat and the methodology proposed by Decker, D'Erasmo and Moscoso Boedo (2016). We compute measures of sector- and firm-specific risk from the the estimated parameters and firm-size residuals of the equation:

$$\Delta w_{\ell sa} = \delta_{sa} + \beta_{1s} \ln (size_{\ell sa}) + \beta_{2s} \ln (age_{\ell sa}) + \varepsilon_{\ell sa} \tag{14}$$

where the outcome variable, $\Delta w_{\ell sa}$, is either earnings growth (baseline) or sales growth (robustness) of firm ℓ in sector s in year a.[15] While sales data is widely available, earnings is likely more relevant to payoffs in the model, and thus we use earnings as baseline and sales as robustness. We control for size and age as those may be known sources of uncertainty. To measure sector-specific risk in each sector and 5-year period, we compute the standard deviation of the estimated annual sector-time fixed effects, δ_{sa}. We estimate idiosyncratic risks for each sector and 5-year period as the time average of the annual cross-sectional dispersion of regression residuals, $\varepsilon_{s\ell a}$.

Table 4 presents the summary of the pooled distribution of the estimated parameters across sector-periods. Idiosyncratic risk accounts for most of the total risk, with a median estimate of 0.03 for sector-specific risk and of 0.18 for idiosyncratic risk . There is also more dispersion in the estimates of idiosyncratic risk, both in terms of the standard deviation of the estimates and their interquartile range. Similarly, idiosyncratic risk is higher and shows

[15]The measure of earnings growth is scaled to the average assets in the current and previous years. The measure of annual sales growth is scaled to the average sales in the current and previous years.

Table 4: Statistics on Estimated Parameters

		Mean	Std.Dev.	P25	P50	P75
Sector and idiosyncratic risk						
earnings growth	σ_{st}	0.04	0.03	0.02	0.03	0.05
	$\sigma_{\varepsilon_{st}}$	0.21	0.11	0.13	0.18	0.28
sales growth	σ_{st}	0.07	0.06	0.04	0.06	0.09
	$\sigma_{\varepsilon_{st}}$	0.29	0.12	0.21	0.28	0.35
Demand proxies						
Δ log(market value)		0.16	0.64	-0.10	0.20	0.48
price-earnings ratio		7.2	2.6	5.2	6.7	8.3

Notes: Statistics are computed across the whole unbalanced panel with each unit of observation being a sector-period. Sector here refers to a 2-digit SIC code. See appendix A.2 for details.

more absolute dispersion than sector risk when we focus on risk proxies based on sales.

The last two rows of Table 4 report statistics on sector-specific demand proxies: an index for market value and a price-earning ratio. Both are computed from Compustat firm-level data and exhibit sector and period variability. Later, we use them to evaluate the adequacy of Assumption 1 about the evolution of the mass of investors across sectors by using two external proxies

Components of model-based decomposition – Next, we obtain the components of the model-based decomposition. We use a product $\times$ sector $\times$ period dataset that includes information on the number of issuances and issuers, along with the estimated parameters σ^2_{st} and $\sigma^2_{\varepsilon_{st}}$, to construct the competition and risk component in Equation (13). We then apply Proposition 3 to estimate the double difference average productivity component a as residual.

In Table 5 we present various statistics of the double difference of log proceeds, $\Delta^{s,t}\log(Y_{st})$, and its estimated components. Note that because we use double differences $\Delta^{s,t}$, we capture relative variations and the average of each variable is zero. The standard deviations show that there is substantial variability across sectors and time in log proceeds and its components. The table also provides cross-sectional correlation between the components. These correlations yield several insights. First, not surprisingly, sectors with higher relative log proceeds have a higher relative average productivity component, as well as a higher competition and risk component. Second, the correlation between the relative average productivity component and the relative competition and risk component is negative, which indicates that sectors that exhibit larger increases in the relative productivity of the financial products ex-

Table 5: Statistics on Components

		Mean	Std.Dev.	Correlations $\Delta^{s,t}Y_{st}$	$\Delta^{s,t}\bar{\chi}_{st}$	$\Delta^{s,t}Z_{st}$	$\Delta^{s,t}L_{st}$	$\Delta^{s,t}I_{st}$
	$\Delta^{s,t}Y_{st} = \Delta^{s,t}\bar{\chi}_{st} + \Delta^{s,t}Z_{st}$	0.00	0.98	1				
Average productivity	$\Delta^{s,t}\bar{\chi}_{st}$	0.00	0.87	0.74	1			
Competition & risk	$\Delta^{s,t}Z_{st}$	0.00	0.67	0.48	-0.24	1		
Number Issuers	$\Delta^{s,t}L_{st}$	0.00	12.41	0.19	0.03	0.24	1	
Number Products	$\Delta^{s,t}I_{st}$	0.00	3.05	0.35	0.08	0.40	0.71	1

Notes: The table provides statistics about (log) proceeds, the components of average productivity and risk and dispersion (as described in Proposition 3), number of issuers, and number of financial products. The first and second columns show the average and standard deviation, respectively. The remaining columns display pairwise correlation coefficients. We use the sector $\times$ period dataset, and for all variables we apply the double-difference operator for sector and period. Sectors are defined with 4-digit SIC codes. Table F2 provides statistics on the double-differences in changes of proceeds (instead of double-differences in levels).

hibit smaller increases in the competition and risk component. This negative correlation is consistent with the trade-off that issuers face in the model between using higher productivity financial products and differentiating themselves from competitors. Third, sectors with higher growth in proceeds and in the competition and risk component also exhibited higher growth in the numbers of issuers and of financial products.

Variance-decomposition – Finally, we use a variance-decomposition procedure to quantify the contributions of the components implied by our model to the dispersion in sectors' proceeds over time. We follow the methodology developed by Eaton, Kortum and Kramarz (2004). This decomposition procedure uses the structure of the model to isolate different margins in the data, without making assumptions about how those margins are related. Specifically, Proposition 3 shows that we can quantify the role of average product productivity ($\Delta^{s,t}\bar{\chi}_{st}$) and the role of competition and risk ($\Delta^{s,t}Z_{st}$). We implement the decomposition by estimating

$$\Delta^{s,t}\bar{\chi}_{st} = \beta^{\text{average productivity}}\Delta^{s,t}Y_{st} + e_{st}$$
$$\Delta^{s,t}Z_{st} = \beta^{\text{competition \& risk}}\Delta^{s,t}Y_{st} + v_{st}.$$

Appendix B discusses two crucial properties of this variance decomposition. First, the terms in the decomposition need not be independent. Second, we do not need to observe all components to identify their impact, as the properties of the estimator mean that all components sum up to 1 (in our case $\beta^{\text{average productivity}} + \beta^{\text{competition \& risk}} = 1$).

Table 6 shows the baseline estimated components $\beta^{\text{average productivity}}$ and $\beta^{\text{competition \& risk}}$

Table 6: Variance Decomposition

	Baseline	Alternatives				
		$\Delta^{s,t}\Delta \log Y$	Demand M.Value	Demand P/E	Issuers	Parameters
Average productivity	0.67	0.64	0.61	0.67	0.57	0.66
Competition and risk	0.33	0.36	0.34	0.33	0.43	0.34
Demand	-	-	0.05	0.00	-	-

Notes: The table presents the results from our decomposition of the (log) proceeds at the sector × period level, as defined in equation (3). The regressions use the baseline sector × period dataset with sectors defined by 4-digit SIC codes. We apply the double difference operator for sector and period. The first component under "Alternatives" applies the decomposition to the double differences first difference in proceeds (instead of levels). The second and third columns apply the decomposition to the market value index and price-earning ratio as proxies for demand. The fourth uses issuances instead of issuers to compute the component of risk and dispersion. The last column uses the alternative parameter estimates of firm- and sector-specific risk based on sales growth.

and the robustness results. Our results indicate that the types of financial products that firms issue explains nearly two-thirds of the cross-section variation in the growth rates of funds raised. Thus, if the proceeds in sector A grow on average 10% more than sector B, then 67% of this growth is attributed to improvements in the productivity of the financial products that firms in sector A are issuing relative to improvements in the productivity of the products that firms in sector B are issuing. In other words, if improvements in the productivity of the products that firms in sector A are issuing would be the same as improvements in the productivity of products that firms in sector B are issuing, then proceeds in sector A would grow on average only 3.4% more than sector B.

We evaluate the robustness of the baseline decomposition across multiple dimensions. First, we apply the decomposition to the double-differences in changes in proceeds (instead of double-differences in levels), and we find little difference in the contribution of the average productivity component. Second, we apply the decomposition using external proxies for the sector-period mass of investors – a market-value index and a price-earning ratio – and find minimal impact on the importance of average productivity. This supports the hypothesis that assumption 1 matches the data well. Third, we calculate an alternative component to capture competition and risk, using the number of issuances rather than the number of issuers. Since some firms issue the same product multiple times over a period, these two variables may differ. We treat each issuance as an independent event, with both variables serving as proxies for the supply of securities. Finally, an alternative estimate of idiosyncratic and sector-specific risk based on sales growth has little impact on the results. This test shows that the alternative measures of risk are highly correlated.[16]

Our estimates of the contribution from the two main components to the variation in the proceeds growth rate are obtained through the lens of the conceptual framework outlined in Section 4. With the observable component ($\Delta^{s,t} Z_{st}$) accounting for one-third of the variation in proceeds growth rate, the model demonstrates significant predictive power with respect to the impact of competitive forces and risk factors. However, since changes in average productivity ($\Delta^{s,t}\bar{\chi}_{st}$) are estimated as residuals, we go a step further and show that this component is associated with the amount and nature of new financial products.

5.2 The Adoption of New Products and Average Productivity

The average productivity of financial products used in sector s at time t can be written such that the allocation of products to the sector is made explicit

$$\bar{\chi}_{st} \equiv \sum_{i \in \mathcal{I}_t} \left(\chi_{ist} \frac{d_{ist}}{\sum_{i \in \mathcal{I}_t} d_{ist}} \right)$$

where $\mathcal{I}_t$ is the set of all products available at time t across all sectors, and d_{ist} is a dummy for whether at least one firm in sector s issues product i at time t. This dummy captures the allocation of products to distinct sectors. To isolate the sources of changes in average productivity between period $t = 0$ (prior to 1985) and $t \geq 1$, we distinguish between financial products available in both periods $\mathcal{I}_t^c$, new products $\mathcal{I}_t^n$ (that is, the set of products in t but not in period 0), and the set of exiting products $\mathcal{I}_t^x$ (that is, the set in period 0 but not in t). Changes in average productivity can then be written as a function of two sets of terms:

$$\begin{aligned}
\Delta\bar{\chi}_{st,s0} = & \sum_{i \in \mathcal{I}_t^c} \left(\chi_{ist} \frac{d_{ist}}{\sum_{i \in \mathcal{I}_t} d_{ist}} - \chi_{is0} \frac{d_{is0}}{\sum_{i \in \mathcal{I}_0} d_{is0}} \right) && \text{Continuing} \\
& + \sum_{i \in \mathcal{I}_t^n} \left(\chi_{ist} \frac{d_{ist}}{\sum_{i \in \mathcal{I}_t} d_{ist}} \right) - \sum_{i \in \mathcal{I}_t^x} \left(\chi_{is0} \frac{d_{is0}}{\sum_{i \in \mathcal{I}_0} d_{is0}} \right) && \text{Entry \& Exit} \qquad (15)
\end{aligned}$$

The first set captures changes in the contribution of continuing products, which are present in both period 0 and $t \geq 1$. The second set of terms includes the effects of changes in the set of available products, so it captures the adoption of new products and the exit of old

[16] In Table F3 in Appendix, we also show the results for different values of μ_ζ; these are quantitatively almost equal. They are equal because the double difference of the component of risk and dispersion is unchanged.

products.

The disaggregation in Equation (15) makes it explicit that new products can affect overall average productivity. In particular, firms find new products appealing if they offer higher productivity compared to their current products. Insights from the model in Section 4 inform us that if firms in a sector do not issue a product, the product does not satisfy the cutoff for productivity $\chi_{st}^{\min}$ defined in Equation (12). This implies that $d_{ist} = 1$ if $\chi_{ist} \geq \chi_{st}^{\min}$, and is zero otherwise. Thus, while we cannot measure the contributions of each of the components in Equation (15) because we cannot observe χ_{ist}, we can make inferences if we observe that a new product was adopted by a sector.

With these insights in mind, we turn to the data and evaluate whether the adoption of new financial products is associated with changes in average productivity, estimated in the previous section. Table 7 shows the regression output from equation $D_{s,t} = \beta X_{s,t} + \text{Controls}_{st} + \alpha_s + \gamma_t + \varepsilon_{s,t}$, where the dependent variable is the double difference in log productivity $\Delta^{s,t}\bar{\chi}$ (or, as robustness, the double difference in first difference of changes in productivity $\Delta^{s,t}\Delta\bar{\chi}$). We use three distinct measures to capture the adoption of new financial products: (1) number of new products (log), $\log(\sum_{i\in\mathcal{I}_t^n} d_{ist})$; (2) share of new products, $\frac{\sum_{i\in\mathcal{I}_t^n} d_{ist}}{\sum_{i\in\mathcal{I}_t} d_{ist}}$, and share of new products novelty-adjusted, $\frac{\sum_{i\in\mathcal{I}_t^n} d_{ist} n_i}{\sum_{i\in\mathcal{I}_t} d_{ist}}$. New products are defined as new products across any sector (Panel A). We also evaluate an alternative definition, where new products are defined as new products in a specific sector (Panel B). All regressions include sector and time fixed effects to account for sector and time-specific confounding factors impacting the independent variables.[17] We also include in the baseline specification, number of issuances (in logs) to account for sector-specific time-variant demand and supply factors.

The results provide evidence of a positive significant association between the adoption of new financial products and the average productivity of the financial products used. Our preferred specification shows that an increase in the share of new products by 10 percentage points is associated with a 4.36% increase in average productivity (Table 7, Panel A, Column 2). When we account for the degree of novelty of the new financial products, we see that an increase in the share of new products novelty-adjusted by 10 percentage points is associated with a 12.12% increase in average productivity (Table 7, Panel A, Column 3). The magnitudes are fairly large, as an increase of one standard deviation in the share of new products (Table F4 in Appendix) is associated with a one-seventh increase in the average

[17]Note that the dependent variable is defined in double differences and as such is already net of sector and time-specific factors.

Table 7: New Financial Products and Average Productivity

Panel A - New Products

Dep. Var.	$\Delta^{s,t}\bar{\chi}$			$\Delta^{s,t}\Delta\bar{\chi}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Ind. Var.	log new	share new	share nov-adj	log new	share new	share nov-adj
Coefficient	0.074*	0.436***	0.982***	0.072*	0.336***	0.953***
	(0.041)	(0.072)	(0.254)	(0.042)	(0.083)	(0.293)
Observations	3,637	3,637	3,634	2,598	2,598	2,595
R-squared	0.203	0.213	0.207	0.072	0.078	0.075
Sector	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y

Panel B - Sector's New Products

Dep. Var.	$\Delta^{s,t}\bar{\chi}$			$\Delta^{s,t}\Delta\bar{\chi}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Ind. Var.	log new	share new	share nov-adj	log new	share new	share nov-adj
Coefficient	0.062	0.948***	0.537***	0.234***	0.780***	0.351
	(0.067)	(0.116)	(0.183)	(0.058)	(0.133)	(0.243)
Observations	3,637	3,635	2,053	2,598	2,595	1,246
R-squared	0.203	0.221	0.355	0.078	0.087	0.250
Sector	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y

Notes: The table presents the regression output from the equation $D_{s,t} = \beta X_{s,t} + \text{Controls}_{s,t} + \alpha_s + \gamma_t + \varepsilon_{s,t}$. The dependent variable is the double difference in productivity $\Delta^{s,t}\bar{\chi}$ in columns (1) to (3), and the double difference in first differences of the productivity component $\Delta^{s,t}\Delta\bar{\chi}$ in columns (4) to (6). Each column's data results from running the regression on different independent variables defined at the sector-period level: Columns (1) and (4) use the log of the number of new products, Columns (2) and (5) use the share of new products, Columns (3) and (6) use the share of novelty-adjusted new products (Table F5 shows results for the different measures of novelty). The independent variables are computed weighting by proceeds of the different products in a particular sector-period (Table F7 in Appendix shows results without weighting). The regressions include number of issuances (log) as controls (Table F6 in Appendix shows results without controls). In Panel A, new products are defined across any sector, while in Panel B, new products are defined as new products within a specific sector. The regressions are based on the baseline sector-period dataset, with sectors classified by 4-digit SIC codes.

quality. The positive association between the adoption of new financial products and growth in access to funds is robust in multiple dimensions. We evaluate the relationship between the first difference in the average productivity component and the first difference in the variables capturing adoption of new financial products, we find that the association is positive and significant (columns 4 to 6). Moreover, we study the relationship when we define new products based on their first time issuance in a sector and find that robust results (Panel B).

Overall, we find strong support that the differential adoption of new financial products is positively associated with the average productivity component.[18] While we cannot establish causality, we posit that the development of new financial products provided investors a higher expected value per unit of risk, and thus raised firms' ability to raise external funding.

5.3 The Adoption of Specialized Products and Average Productivity

The framework introduced in Section 4 allows financial products to be horizontally differentiated across sectors, as their productivity is sector-specific. In other words, the same product might be more useful in some sectors and less in others. For instance, a product that requires collateral may have a higher productivity for firms in sectors with many physical assets than for those in sectors that rely on intangible assets.[19] Indeed, the rank correlations calculated in Section 3.2 provide empirical support for this sectoral differentiation.

We proceed to evaluate how this feature may impact the average productivity component. The component can increase either through the adoption of a new product that has high productivity across many sectors and/or through the adoption of a new product that is particularly well-suited to that particular sector. To see this, consider the average quality of the product i across sectors $\bar{\chi}_{it} \equiv \frac{1}{S}\sum_s \chi_{ist}$, and note that we can express the average quality of financial products in a sector as

$$\bar{\chi}_{st} = \sum_{i \in \mathcal{I}_t} \left(\bar{\chi}_{it} \frac{\chi_{ist}}{\bar{\chi}_{it}} \frac{d_{ist}}{\sum_{i \in \mathcal{I}_t} d_{ist}} \right). \tag{16}$$

Some products have high $\bar{\chi}_{it}$ because $\bar{\chi}_{ist}$ is high across many sectors, making them more likely to be widely adopted. We will refer to those as "standardized" products. Other products have low $\bar{\chi}_{it}$, but there are sectors where χ_{ist} is high, resulting in the adoption of these products in those specific sectors in equilibrium. Thus, a product may be issued by many firms in one sector but by only a few—or none at all—in another. We will refer to these as "specialized" products.[20]

We evaluate empirically the association between changes in average productivity and

[18] Note that firms in a given sector do not issue a particular financial product as a result of two observationally equivalent situations. First, not all financial products may be available to issuers across all sectors. Second, the financial products may be available to issuers but they may choose not to use them.

[19] Babus, Marzani and Moreira (2023) presents indirect evidence based on a narrower sample of public firms, indicating that firms relying on intangible assets issue new financial products more so than other firms. This suggests that new financial products can offer more customized solutions that align with the

Table 8: Specialized and Standardized New Products and Average Productivity

Panel A - New Products

Dep. Var.	$\Delta^{s,t}\bar{\chi}$					
	Log new		Share new		Share novelty-adj	
Ind. Var.	specialized	standardized	specialized	standardized	specialized	standardized
	(1)	(2)	(3)	(4)	(5)	(6)
Coefficient	0.140**	0.024	1.158***	0.332***	4.099***	0.558**
	(0.067)	(0.042)	(0.216)	(0.075)	(0.684)	(0.220)
Observations	3,637	3,637	3,637	3,637	3,634	3,634
R-squared	0.204	0.202	0.210	0.208	0.211	0.204
Sector	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y

Panel B - Sector's New products

Dep. Var.	$\Delta^{s,t}\bar{\chi}$					
	Log new		Share new		Share novelty-adj	
Ind. Var.	specialized	standardized	specialized	standardized	specialized	standardized
	(1)	(2)	(3)	(4)	(5)	(6)
Coefficient	0.121*	-0.011	1.147***	0.471***	1.700***	0.044
	(0.066)	(0.066)	(0.213)	(0.104)	(0.339)	(0.178)
Observations	3,637	3,637	3,635	3,635	2,053	2,053
R-squared	0.203	0.202	0.211	0.208	0.363	0.351
Sector	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y

Notes: The table presents the regression output from estimating the equation $\Delta^{s,t}\bar{\chi} = \beta X_{s,t} + \text{Controls}_{s,t} + \alpha_s + \gamma_t + \varepsilon_{s,t}$. The dependent variable is the double difference in the productivity component. Each column's data results from running the regression on different independent variables ($X_{s,t}$) at the sector-period level. Columns (1) and (2) display the log of the number of new specialized and standardized products, respectively. Columns (3) and (4) show the share of new specialized and standardized products, respectively. Columns (5) and (6) report the share of novelty-adjusted new specialized and standardized products, respectively. Specialized products are those used by up to 5 sectors, while standardized products are used by more than 5 sectors. The independent variables are computed weighting by proceeds of the different products in a particular sector-period (Table F11 in Appendix shows results without weighting). The regressions include number of issuances (log) as controls (Table F10 in Appendix shows results without controls). In Panel A, new products are defined across any sector, whereas in Panel B, new products are defined as new products within a specific sector. The regressions use the baseline sector-period dataset, with sectors classified by 4-digit SIC codes.

the composition of standardized versus specialized products that firms in different sectors use. We use the allocation of securities to sectors to proxy for whether they are likely "standardized" or "specialized" products. In the data, we classify products as "specialized"

unique financing requirements of specific firms.

[20] We adopt the terms "standardized" and "specialized' goods from Holmes and Stevens (2014).

if they are used by at most five sectors and "standardized" if they are used by more than five sectors. Under this classification, there are 436 specialized products used by 235 sectors. For each sector $\times$ period, we compute the number of standardized/specialized products, the share of new standardized/specialized products, and the share of new standardized/specialized products novelty-adjusted. We use regression analysis (as in Section 5.2) that relies on within-sector and time-period variation to evaluate the association between these variables and average productivity.

Table 8 shows that sectors that use relatively more new specialized products have higher increases in the average productivity component. The use of a large amount of new standardized products also have a positive association with the component, but have a significantly lower association than specialized new products. Our preferred specification shows that an increase in the share of new specialized products by 10 percentage points is associated with a 11.48% increase in average productivity, and an increase in the share of new standardized products by 10 percentage points is associated with a 3.32% increase (columns 3 and 4).[21] When we account for the degree of novelty of the new financial products, the results also point out to a larger effect of specialized. At the same time, the novelty distribution of specialized products is indistinguishable from that of standardized products (Figure E7 in Appendix). This suggests that changes in the average productivity at sector level are not explained by significant changes in security design. The stronger positive association between the adoption of new specialized financial products and growth in access to funds is robust to using alternative proxies to "specialized" and "standardized" (Table F8 in Appendix). Moreover, we find similar results when using first differences (Table F9 in Appendix), defining new products based on their first time issuance in a sector and find that robust results (Panel B), using alternative controls and weighting schemes (Tables F10 and Table F11 in Appendix).

Our results are consistent with the hypothesis that when innovation generates new products that are attractive to many sectors we are not able to identify significant impacts on average productivity differences across sectors. These findings also indicate that sectors utilizing specialized financial products exhibit a greater capacity to raise funds compared to sectors relying on generic products.[22] We interpret this as evidence that while specialized products may represent minor modifications to generic products, they are tailored to meet

[21]Note that the differential impact of specialized and standardized products is significant (see Table F12 in Appendix).

[22]Note that because we use within-sector and time-period variation, we cannot rule out that new standardized products do not have a large impact on the firms' overall ability to raise funds via security issuance.

the specific needs of firms within a particular sector.

6 Conclusion

This paper has examined the role of innovation in expanding the set of contracts that firms can issue and in its contribution to firms ability to raise funds. We use data about the issuance of corporate securities to build a dataset that allows us to measure the usage of distinct financial products over the last three decades. We explore the role of new financial products – identified as financial products created during the period of analysis – and compare their importance and characteristics with those of products that already existed. We document that the share of funds raised through new financial products is significant. Although many of these products are not widely adopted, they represent an important means of raising funds for the firms that do use them.

To interpret these facts, we develop a model in which firms across sectors choose strategically which financial products they will offer to investors. Financial products are characterized by a productivity component that captures how the product impacts the payoffs of the claims issued by firms in a sector. The model allows us to account for multiple margins affecting a firm's ability to raise funds. The model design allows us to infer patterns about the productivity of financial products, which are not directly observed in the data, from our observations of product allocation. Through the lens of our model, we estimate that the average productivity of financial products plays a crucial role in explaining differences across sectors in raising funds. We also find that innovations represented in specialized new products are most responsible for increases in average productivity. Our results indicate that innovation in the financial market is akin to innovation in consumer markets, which tends to result not just in improvements in the productivity of standardized products, but also in increasing variety in a given market as products become more specialized. These findings are relevant to the vibrant literature studying the role of innovation in the process of economic growth and structural change.

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Appendix

A Data Set Construction

A.1 SDC Platinum

We use data from the Global New Issues modules of the SDC Platinum Dataset provided by Refinitiv. The database covers all public, private and Rule 144A issuances of securities with maturity higher than one year (where applicable) starting in 1970 and includes issuances of non-derivative securities. For example, the dataset includes equity, bonds and medium term notes, while it excludes options, futures contracts and commercial paper.

We select issuances originated by the U.S. non-financial corporate sector both in the U.S. and abroad, and thus exclude from the analysis all issuances where the issuer parent is not headquartered in the U.S., is a financial corporation or is part of a government, federal agency or federally sponsored institution. We also exclude shelf registrations that have not yet been issued, withdrawn registrations and issuances with missing information on proceeds, security type or bookrunner. Finally, we explicitly exclude transactions that appear to be syndicated loans wrongly classified as issuances of securities.

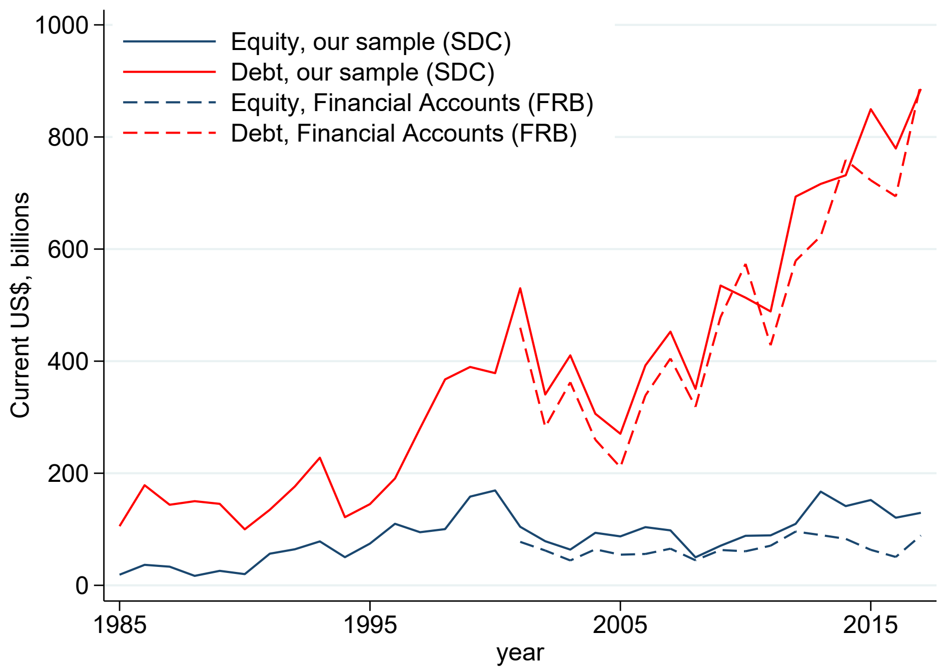
We assess the representativeness of our data by comparing the total annual proceeds with those reported in the Financial Accounts of the United States by the Federal Reserve Board, which we match to a large extent. In figure A1 we show such comparison.

To make sure the coverage over time is homogeneous we exclude from the analysis the period before 1985. The selected sample comprises 72,190 issuances of 751 distinct security types by 17,851 firms, across 847 4-digit SIC sectors over the period 1985-2014. We deflate proceeds using CPI-U price index from the Bureau of Labor Statistics. We then collapse this dataset at the sector-type-period level with periods of 5 years, obtaining an unbalanced panel of 20,400 observations. Summary statistics for this datasets are presented in Table 1.

A.2 Compustat

For the decomposition in section 4.4.1 we rely on an external data source of risk and demand proxies. Since risk in our model materializes within issuers as volatility in cashflow, we make use of Compustat Fundamentals Annual data to obtain proxies for such risk. We obtain annual observations of sales, earnings, total assets, and market capitalization for firms in the U.S. non-financial corporate sector. We start with the full sample starting in 1960 to

Figure A1: Data coverage vs. Financial Accounts



Notes: The figure shows annual proceeds from issuances of stocks and bonds in our sample and the corresponding counterparts as reported in the Financial Accounts by the Federal Reserve Board.

define age as the years since each firm first shows up in Compustat and then exclude all observations prior to 1985 and post 2014. As a measure of size we use total assets.

A.2.1 Key Variables

In equation 14 we use two different versions of cash flows growth. First we use sales growth, which has the least missing values, defining

$$\Delta z^{(1)}_{i,s,t} = \frac{sales_{i,s,t} - sales_{i,s,t-1}}{\frac{1}{2}\left(sales_{i,s,t} + sales_{i,s,t-1}\right)} \tag{A.1}$$

Second, we use earnings growth scaled by assets as follows

$$\Delta z^{(2)}_{i,s,t} = \frac{earnings_{i,s,t} - earnings_{i,s,t-1}}{\frac{1}{2}\left(assets_{i,s,t} + assets_{i,s,t-1}\right)} \tag{A.2}$$

A.2.2 Sector Variance Estimation

The outcomes of interest of such regressions are estimated sector-time fixed effects and the residuals, which we use to obtain estimates of cash-flow risk as follows

$$\hat{\sigma}_{s,p} = \left[\frac{1}{5} \sum_{t \in p} \left(\hat{\delta}_{s,t} - \frac{1}{5} \sum_{t \in p} \hat{\delta}_{s,t} \right)^2 \right]^{\frac{1}{2}} \tag{A.3}$$

$$\hat{\sigma}_{\varepsilon_s,p,i} = \left[\frac{1}{5} \sum_{t \in p} \left(\hat{\varepsilon}_{i,s,t} - \frac{1}{5} \sum_{t \in p} \hat{\varepsilon}_{i,s,t} \right)^2 \right]^{\frac{1}{2}} \tag{A.4}$$

$$\hat{\sigma}_{\varepsilon_s,p} = Median \left\{ \hat{\sigma}_{\varepsilon_s,p,i} \right\}_{i \in s} \tag{A.5}$$

where $t \in p$ means that year t is in the 5-year period p and $i \in s$ means that firm i operates in sector s.

The estimates are computed with sectors defined as a 2-digit SIC code. We do not have enough Compustat firms at a higher sector disagregation. Because our analysis is conducted at 4-digit SIC codes, we use the same estimates of sector and idiosyncratic risk for 4-digit sectors within 2-digit SIC codes.

B Variance Decompositions

In this section, we present the variance decompositions to quantify precisely the contribution of the components implied by our model to the dispersion of sectors' proceeds over time. We follow the methodology developed by Eaton, Kortum and Kramarz (2004). These decompositions use the structure of the model to isolate different margins in the data without making assumptions about how those margins are related.

B.1 Framework for Variance Decompositions

Consider an hypothetical decomposition of just two components, where we have the following identity

$$Y_j \equiv X_{1j} + X_{2j} \tag{B.1}$$

The variance of Y is given by

$$Var(Y_j) = Var(X_{1j}) + Var(X_{2j}) + 2Cov(X_{1j}, X_{2j}) \tag{B.2}$$

In the case of all components being observable, we can implement the decomposition of variance of Y by estimating by OLS the following set of equations

$$X_{1j} = \beta_{10} + \beta_1 Y_j + \upsilon_{1j}$$
$$X_{2j} = \beta_{20} + \beta_1 Y_j + \upsilon_{2j}$$

where the estimated OLS coefficients are given by the following

$$\hat{\beta}_1 = \frac{Cov(X_{1j}, Y_j)}{Var(Y_j)} = \frac{Var(X_{1j}) + Cov(X_{1j}, X_{2j})}{VarY_j}$$
$$\hat{\beta}_2 = \frac{Cov(X_{2j}, Y_j)}{Var(Y_j)} = \frac{Var(X_{2j}) + Cov(X_{1j}, X_{2j})}{VarY_j}$$

Some key implications can be derived. First, the properties of OLS are such that the sum of $\hat{\beta}_i$ equals to 1. To see that note that

$$\sum \hat{\beta}_i = \frac{Var(X_{1j}) + Var(X_{2j}) + 2Cov(X_{1j}, X_{2j})}{VarY_j} = \frac{Var(Y_j)}{Var(Y_j)} = 1$$

Second, note that the terms in the decomposition do not need to be independent. For example, X_{1j} and X_{2j} can be correlated. The estimated coefficients of the OLS regressions will split the covariance equally among components.

B.2 Proof of Proposed Decomposition

Consider the equality derived from our model that holds every time period t

$$\log Y_{st} = 2\log\left[\frac{\sum\limits_{i\in I_{st}} \chi_{ist}}{I_{st}}\right] + \log \frac{\sum\limits_{i\in I_{st}} \frac{\omega_{ist}}{L_{ist}}\Lambda_{ist}}{\left[\sum\limits_{i\in I_{st}} \frac{\omega_{ist}}{L_{ist}}\left(1-\Lambda_{ist}\right)\right]^2} + \log\frac{1}{\left(\sigma_{st}^2 + \sigma_{\varepsilon_{st}}^2\right)} + \log\left[\frac{\eta_{st}}{\gamma}\right] \tag{B.3}$$

where the investors demand component can be re-written as $\log\eta_{st} - log\gamma$. The first term in the demand component is assumed to be $\log\eta_{st} = \log\eta_s + \log\psi_t$ (under the assumption of additive separability of the (log) mass of investors). The second term depends solely on parameters and does not affect the variance.

Consider demeaning the proceeds relative to the average proceeds in the sector, and then demeaning it across time.

$$\Delta^{s,t} \log Y_{st} = \left(\log(Y_{st}) - \overline{\log(Y_s)}\right) - \overline{\left(\log(Y_{st}) - \overline{\log(Y_s)}\right)} \tag{B.4}$$

where $\Delta^{s,t}$ stands for the double difference operator for sector s and over time t. The demand component under the assumption above is

$$\Delta^{s,t} X_{1st} = \left(X_{1st} - \overline{X_{1s}}\right) - \overline{\left(X_{1st} - \overline{X_{1s}}\right)} = 0 \tag{B.5}$$

And thus, we have that double differences in proceeds are a function of the productivity of proceeds and a component capturing competition and risk.

$$\Delta^{s,t} \log Y_{st} = \Delta^{s,t} 2 \log \left[\frac{\sum\limits_{i \in I_{st}} \chi_{it}}{I_{st}} \right] + \Delta^{s,t} \left[\log \frac{\sum\limits_{i \in I_{st}} \frac{\omega_{ist}}{L_{ist}} \Lambda_{ist}}{\left[\sum\limits_{i \in I_{st}} \frac{\omega_{ist}}{L_{ist}} \left(1 - \Lambda_{ist}\right) \right]^2} + \log \frac{1}{\left(\sigma_{st}^2 + \sigma_{\varepsilon_{st}}^2\right)} \right] \tag{B.6}$$

B.3 Application of Decomposition

Our model indicates that the double difference of proceeds can be decomposed into two components. Mapping to the general specification above, we have that

$$\begin{aligned}
Y_j &= \Delta^{s,t} \log Y_{st} \\
X_{1j} &= \Delta^{s,t} 2 \log \left[\frac{\sum\limits_{i \in I_{st}} \chi_{it}}{I_{st}} \right] \\
X_{2j} &= \Delta^{s,t} \left[\log \frac{\sum\limits_{i \in I_{st}} \frac{\omega_{ist}}{L_{ist}} \Lambda_{ist}}{\left[\sum\limits_{i \in I_{st}} \frac{\omega_{ist}}{L_{ist}} \left(1 - \Lambda_{ist}\right) \right]^2} + \log \frac{1}{\left(\sigma_{st}^2 + \sigma_{\varepsilon_{st}}^2\right)} \right]
\end{aligned}$$

C Novelty

We rely on methods from the literature on natural-language processing for our similarity metric. The baseline algorithm has the following steps:

1. Collect representative documents of financial products
2. Document vectorization
3. Compute similarity score between pairs of products
4. Compute novelty

C.1 Representative Documents

We use two sets of representative documents. The first, is the SDC description of the financial product. The second, we obtain from studying multiple sources to describe the nature of the different financial products. We considered Investopedia website, securities prospectus; and several other Ad-hoc websites. Investopedia offers the the most-comprehensive and standardized descriptions of securities contracts. Moreover, we decided not to use multiple sources simultaneously as the measures of similarity would then capture superficial differences in the source material. To find the best match of a financial product to an Investopedia article, we web-scrapped the website and manually selected the articles to find the best match for each product. The selection involved multiple research assistants to ensure that the selection was as not driven by idiosyncratic bias.

The raw data consist of 1,147 unique names of financial products.[23] Among these, 130 products have an exact article on Investopedia (i.e., the article matches the name of the security in the SDC exactly); 57 have a unique article that is the closest match; 516 are described using a combination of two articles; and 445 are described using a combination of three articles. Overall, we utilize a total of 375 distinct Investopedia articles (called throughout as blocks).[24] Figure C1 shows some examples. In particular, we selected block that are associated with products – *Auction Market Preferred Stock*, *Equipment Trust Notes*, *Principal Exchange Rate Linked Securities*, and *Pay-In-Kind Notes*, among other. Within

[23]This sample is larger than the one used in our analysis because the method was developed for all securities issued since 1970, without restricting it to products issued after 1985 or to those issued by the non-financial corporate sector.

[24]The mapping between products and blocks is available upon request, as well as robustness exercises on exact vs. non-exact assignments and on the number of blocks.

the Investopedia article, we selected the body text by filtering the relevant sections. In particular, we scrape each web page associated with a block using the Python package "BeautifulSoup".

Figure C1: Examples of Investopedia Blocks

What Is a Payment-In-Kind (PIK) Bond?

A payment-in-kind (PIK) bond refers to a type of bond that pays interest in additional bonds rather than in cash during the initial period. The bond issuer incurs additional debt to create the new bonds for the interest payments. Payment-in-kind bonds are considered a type of deferred coupon bond since there are no cash interest payments during the bond's term.

The risk of default by PIK bond issuers tends to be higher, which is why they normally have higher yields. The majority of investors who park their money in PIK bonds are institutional investors.

KEY TAKEAWAYS

- A payment-in-kind bond pays interest in additional bonds rather than in cash during the initial period.
- PIK bonds are usually issued by financially distressed companies.
- These bonds may have low ratings and normally pay interest at a higher rate.
- Although they may provide some financial relief, PIK bonds add to liquidity problems as the debt has to be paid off at some point.

Understanding Payment-In-Kind (PIK) Bonds

Payment-in-kind is used as an alternative way of paying cash for a good or service. With a payment-in-kind bond, no cash interest payment is made to the bondholder until the bond is redeemed or the total principal is repaid at maturity. It is a form of mezzanine debt that lessens the financial burden of making cash coupon payments to investors. On the dates when the coupon payments are due, the bond issuer pays the accrued interest on the PIK debt by issuing additional bonds, notes, or preferred stock. The securities used to settle the interest are generally identical to the underlying securities, but on many occasions, they may have different terms. Because there is no regular income,

What Is an Extendable Bond?

An extendable bond, or extendable note, is a long-term debt security that includes an option that allows the bondholder to extend its initial maturity to a later date. [1]

KEY TAKEAWAYS

- An extendable bond is a long-term debt security that gives bondholders the option to extend its initial maturity to a later date. [1]
- Extendable bonds can allow investors to take advantage of periods of declining interest rates without assuming the risk involved with long-term bonds.
- The price of an extendable bond is the price of a non-extendable bond plus the value of the extendable option. [2]

Understanding Extendable Bonds

An extendable bond is a bond with an embedded option that gives bondholders, or issuers, the right to extend the maturity of the security. It may be seen as a combination of a straight shorter-term bond and a call option to purchase a longer-term bond. Since extendable bonds contain an option to extend the maturity date, a feature that adds value to the bond, they sell at a higher price, with a lower coupon rate, than non-extendable bonds. [2]

When the option to extend the maturity is given to the bond investor, the bond is priced as a put bond. If the option to extend maturity lies in the hands of the issuer, the bond is priced as a callable bond. Depending on the specific terms of the extendable bond, the bondholder, the bond issuer, or both parties may have one or more opportunities to defer the repayment of the bond's principal, during which time interest or coupon payments continue to be made. Additionally, the bondholder or issuer may have the option to exchange the bond for one with a longer maturity, at an equal, or higher, rate of interest. [2]

What Is Auction Market Preferred Stock (AMPS)?

Auction market preferred stock (AMPS) refers to preferred equity shares that have interest rates or dividends that are periodically reset through Dutch auctions. The interest rate on an AMPS issue is reset periodically through such auctions, typically at intervals of every 7, 14, 28, or 35 days. [1]

Auction market preferred stock is also known as auction-rate preferred stock.

KEY TAKEAWAYS

- Auction market preferred stock (AMPS) is a type of preferred shares featuring a variable dividend yield.
- The dividend rate on an AMPS typically resets every one to five weeks via a Dutch auction.
- A Dutch auction is a public auction in which investors place bids for the amount of the offering they are willing to buy and the price they are willing to pay.

Understanding Auction Market Preferred Stock (AMPS)

Adjustable preferred stock shares much of the same attributes as traditional, or "fixed-rate" preferred shares. In both cases, corporations must first pay out dividends to preferred stockholders before paying out any dividends to common stock shareholders. [2] But unlike regular preferred shares, the value of the dividend from the adjustable preferred share is set by a predetermined mechanism to move with rates, and because of this flexibility preferred prices are often more stable than fixed-rate preferred stocks. In the case of AMPS, this mechanism is in the form of a Dutch auction. [3]

Institutional borrowers began issuing auction-rate securities in the 1980s when

What are Premium Adjustable Convertible Securities?

Premium Adjustable Convertible Securities (PEACS) are debt instruments that combine a coupon paying bond with the option to convert the bond into common stock at a set price.

KEY TAKEAWAYS

- Premium Adjustable Convertible Securities (PEACS) combine features of debt and equity.
- PEACS pay a coupon like other bonds, though they come with the option to convert the instrument into common stock at a set price.
- PEACS give investors access to interest and principal payments without sacrificing the chance to participate in the company's capital appreciation.

Understanding PEACS

Premium Adjustable Convertible Securities (PEACS) are often described as hybrid securities because they combine features of debt and equity, converting to ordinary shares at a set date based on a predetermined ratio.

Hybrid securities generally pay a rate of return, which could be fixed or variable, for a certain predetermined period. However, they also contain characteristics of an equity investment, which means there is an increased element of risk, as well.

Convertible securities typically offer a guaranteed interest payment at a specified rate, along with a par value that is achieved at maturity. Unlike a standard bond, however, a convertible security offers the option for the holder to transform the debt into equities if they so choose.

What Is an Equipment Trust Certificate?

An equipment trust certificate (ETC) refers to a debt instrument that allows a company to take possession of and enjoy the use of an asset while paying for it over time. The debt issue is secured by the equipment or physical asset. During this time, the title for the equipment is held in trust for the holders of the issue.

ETCs were originally put in place to finance the purchase of railway cars, but are now used in the sale and purchase of aircraft and shipping containers.

KEY TAKEAWAYS

- An equipment trust certificate refers to a debt instrument that allows a company to take possession of and enjoy the use of an asset while paying for it over time.
- Investors supply capital by buying certificates, allowing a trust to be set up to purchase assets that are then leased to companies.
- After the debt is satisfied, the asset's title is transferred to the company.
- ETCs are commonly used by airlines for the purchase of aircraft.

Understanding Equipment Trust Certificates

Equipment trust certificates are medium- to long-term debt instruments that allow a company to use an asset while they pay for it over time. A trust is set up which creates the certificate. Investors can then purchase and hold these certificates. The capital raised from investors allows the trust to purchase the asset, which is then leased to a company. The trust receives payments from the lessee and distributes them among investors or certificate holders. The terms of the agreement are set out at the beginning of the lease relationship including

What Is a Principal Exchange Rate Linked Security (PERL)?

A principal exchange rate linked security (PERL) is a type of investment in debt that pays interest semiannually and has a yield that is linked to foreign exchange rates. That is, the principal repayment amount is determined by the exchange rate of a certain currency in comparison with the U.S. dollar at the time the repayment is due.

Many buyers of PERLs are companies that see this type of debt security as a means of hedging against fluctuations in foreign exchange rates. They also may be purchased by speculators who think they know which way a particular foreign currency is going to move in price.

KEY TAKEAWAYS

- A PERL is a type of bond that is bought in U.S. dollars and pays interest in U.S. dollars but the final repayment amount is determined in a second currency.
- The yield on the PERL will decrease if the U.S. dollar appreciates against the other currency.
- There also is a reverse PERL which increases in yield if the U.S. dollar appreciates against the other currency.

Understanding Principal Exchange Rate Linked Securities (PERLs)

PERLs are debt securities or debt instruments that are bought and sold between two parties. They pay the buyer semi-annually in amounts that are determined by the exchange rate of a specific currency against a base currency, usually the U.S. dollar.

That makes a PERL a type of dual currency bond which pays the coupon and the principal in the base currency while having the principal payment vary according

C.2 Document Vectorization

We build a vectorized definition for each financial product (f_i) using relevant information scraped from the article. Vectors of terms result from concatenating all fields into one document, followed by parsing and lemmatizing algorithms. This type of method of natural language processing is called "bag-of-words" model. Table C1 shows the description of each vectorization we use in the analysis. Below, we present details.

Table C1: Model Description

	n-grams	Max freq (% of doc)	Min freq (# of counts)	Stop words	Lemmati-zation	Feature (#)
Model 1	1-grams	70	2	yes	no	6,789
Model 1'	1-grams	70	2	yes	yes	4,645
Model 2	1-grams and 2-grams	70	2	yes	no	67,245
Model 3	1-grams and 2-grams	95	2	no	no	75,323

i) Concatenating – Using the results from the web scraping, we construct the text data. Since each security has at least one block, we assign the scraping results to each security based on its blocks. We append the security name ten times to its text data. This procedure assigns ten times more weight to the security name compared to the Investopedia description of the security type.

ii) Token pattern and strip accents – A token Pattern defines what a token is made of. In our analysis, to focus on "English" words in a document, we define a token pattern so that it eliminates numbers and a single character word. Each token generated from the pattern is used as a basic unit when a parsing method constructs n-grams. Also, in tokenizing, we strip the accent of words based on ASCII.

iii) n-grams – In general, n-grams refer to a set of n-consecutive tokens which are generated from a token pattern. In Model 1 and Model 1' in which we use only 1-grams, the unit of tokens is the same as the basic tokens. In Model 2 and Model 3, while we still keep using the basic tokens, we add a set of two consecutive basic tokens as tokens in the vectorization.

iv) Lemmatization – To lemmatize each token, we use WordNetLemmatizer, a module of the NLTK Python package (nltk.org), which utilizes the WordNet lexical database (wordnet.princeton.edu). We implement lemmatization for each token in terms of all possible cases: nouns, verbs, adjectives, adverbs, and satellite adjectives.

v) Stopwords – Stopwords play a role in eliminating words through tokenization, which do not have useful information but appear frequently in a document, such as "the", "is", and "they". We use the English dictionary as a list of stopwords, which is provided by TfidfVectorizer, a module of the scikit-learn Python package. [25] We manually add the following words to the dictionary: (Tex syntax) text, textbf, frac, left, right, sqrt, times, end; (Pronoun Contraction) theyall, theyare, theyll, theyre, theyve, youall, youare, youave, youll, youre, youve; yes; wasnt The total number of the user-defined stopwords list amounts to 339.

In addition, we can reduce the number of words by setting the maximum and minimum frequency thresholds. It generates a document-specific list of stopwords whose frequencies fall out of the bound. In our analysis, we set the maximum at 70% for Model 1, Model 1', and Model 2, and at 95% for Model 3. We use the common minimum, 2 frequencies, for all models.

Table C2 summarizes the numbers of the user-defined stopwords and the stopwords ignored due to the frequency conditions. Model 1 ignores 1,844 words due to the frequency limits. Model 1' has 1,385 words, implying that lemmatization reduces the number of stopwords as well as that of tokens. Model 2 and Model 3 eliminate 34,764 and 32,482, respectively since 2-grams are likely to generate tokens which appear only once.

Table C2: Number of Stopwords

	User-Defined	Frequency Limit
Model 1	339	1,844
Model 1'	339	1,385
Model 2	339	34,764
Model 3	0	32,482

vi) Word vector normalization – After tokenizing and counting processes, the text data for security types are converted into a $K \times M$ matrix. Its entry c_{km} indicates how many times a token appears in a security document where $k \in \{1, \ldots, K\} = \mathcal{K}$ represents a security

[25] The version of scikit-learn is 1.3.0.

in our data and $m \in \{1, \ldots, M\} = \mathcal{M}$ represents a token. The matrix can be very sparse since most tokens are likely to be associated with specific security documents, respectively. Alternatively, most tokens are not used across many security documents, which helps us distinguish differences among security types. Although, there are still some commonly used tokens across the documents.

Thus, to account for the fact that more common words tend to be less informative and vice versa, we use a word-based weighting scheme called total-frequency-inverse-document-frequency (tf-idf) (Aizawa, 2003). A number of possible functional forms could be used here, but we choose the commonly used sublinear form

$$w_m = \log\left(\frac{K+1}{d_m+1}\right) + 1 \quad \text{where} \quad d_m = \sum_{k=1}^{K} \mathbf{1}\left[c_{km} > 0\right]$$

This formulation implies that if a word appears in all documents, we put a weight of one on the word, while those appearing in fewer documents have larger weights.

Using the above weights, we finally obtain a weighted, ℓ^2-normalized word frequency f_{km}

$$f_{km} = \frac{w_m c_{km}}{\sqrt{\sum_{m'} (w_{m'} c_{km'})^2}}.$$

vii) Dimensionality reduction We implement the dimensionality reduction to the word frequency matrix we construct above, mainly for removing the noise in the text data. To reduce the dimension, we use the truncated Singular Value Decomposition (SVD) known as Latent Semantic Analysis (LSA) instead of Principal Component Analysis (PCA) since the matrix is highly likely to be sparse. In the truncated SVD, we first decompose the matrix $\mathbf{X}$ into

$$\mathbf{X} = \mathbf{U}\begin{pmatrix} \mathbf{D}_{R\times R} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{pmatrix}\mathbf{V}' = \sum_{r=1}^{R} \sigma_r \mathbf{u}_r \mathbf{v}_r'$$

where $\mathbf{D}$ is a diagonal matrix of singular values which are arranged in the descending order, $\sigma_1 > \sigma_2 > \cdots > \sigma_R$. Using the arbitrary n largest singular values, we approximate $\mathbf{X}$ as

$$\mathbf{X} \approx \mathbf{X}_n = \sum_{r=1}^{n} \sigma_r \mathbf{u}_r \mathbf{v}_r'.$$

In our analysis, we choose n so that the components extracted from the dimensionality reduction explain 85% of the variance of the original data. If the noise is randomly distributed, we expect it would not explain the data. This implies that the noise is reflected in small singular values. Thus, we can remove the noise using the truncated SVD.

C.3 Similarity Score between Products

We use the cosine similarity to measure the pairwise similarity between all security types, using the matrix after dimensionality reduction. Specifically, we define the similarity as the cosine of the angle between the two vectors:

$$\cos\theta_{ij} = \frac{\sum_{r=1}^{n} \tilde{f}_{ir}\tilde{f}_{jr}}{\sqrt{\sum_{r=1}^{n} \tilde{f}_{ir}^2}\sqrt{\sum_{r=1}^{n} \tilde{f}_{jr}^2}}, \qquad i,j \in \mathcal{K}.$$

The similarity measure is symmetric, implying that $\cos\theta_{ij} = \cos\theta_{ji}$. Also, by construction, the similarity measure belongs to the interval $[-1, 1]$ since some element $\tilde{f}_{ir}$ takes a negative value due to dimensionality reduction. We normalized the index to lie on the interval $[0, 1]$ as follows

$$s_{ij} = \frac{\cos\theta_{ij} - \min(\cos\theta_{ij})}{\max(\cos\theta_{ij}) - \min(\cos\theta_{ij})} \tag{C.1}$$

Table C3 provides statistics of the similarity scores. Overall, the four different methods have very high correlations and the main difference seem to be differences in level.

Table C3: Statistics on Similarity scores

			Correlations			
	Mean	Std.Dev.	Method 1	Method1'	Method 2	Method 3
Method 1	0.376	0.114	1			
Method 1'	0.264	0.126	0.944	1		
Method 2	0.281	0.102	0.948	0.920	1	
Method 3	0.314	0.106	0.930	0.908	0.972	1

Table C4 provides the similarity scores under the four methods for a sample of ij pairs. We selected a heterogeneous set of products comprised of *Auction Market Preferred Stock*, *Equipment Trust Notes*, *Principal Exchange Rate Linked Securities*, and *Pay-In-Kind Notes*, and provide examples of high and low similarity for each.

Table C4: Examples of Similarity Scores

		Model 1	Model 1'	Model 2	Model 3
Flexible Auction Preferred Shares	Auction Market Preferred Stock	0.9954	0.9992	0.9896	0.9899
Convertible Auction Preferred	Auction Market Preferred Stock	0.9148	0.9034	0.8616	0.8444
Auction Rate Notes	Auction Market Preferred Stock	0.6616	0.7473	0.4525	0.4443
Auction Rate Debentures	Auction Market Preferred Stock	0.6194	0.5483	0.4292	0.4260
Flexible Money Market Preferred Stock	Auction Market Preferred Stock	0.5667	0.4358	0.4184	0.4163
Pay-In-Kind Preferred Stock	Auction Market Preferred Stock	0.5198	0.3788	0.4025	0.3786
Premium Income Equity Securities	Auction Market Preferred Stock	0.3000	0.1844	0.2285	0.2432
Pay-In-Kind Notes	Auction Market Preferred Stock	0.2922	0.1883	0.2228	0.2292
Equipment Trust Notes	Auction Market Preferred Stock	0.2877	0.1750	0.2197	0.2263
Principal Exchange Rate Linked Securities	Auction Market Preferred Stock	0.2865	0.1741	0.2144	0.2198
Equipment note Pass-Through Certificates	Equipment Trust Notes	0.8552	0.7938	0.8475	0.8419
Guaranteed Equip Trust Certs	Equipment Trust Notes	0.7068	0.7761	0.6969	0.7018
Equipment Lease Notes	Equipment Trust Notes	0.6401	0.5111	0.6425	0.6671
Mortgage-Backed Notes	Equipment Trust Notes	0.5907	0.3618	0.4835	0.5169
Pay-In-Kind Notes	Equipment Trust Notes	0.5867	0.3298	0.4430	0.4689
Aircraft Leasing	Equipment Trust Notes	0.5599	0.5574	0.3259	0.3768
Leveraged Lease Notes	Equipment Trust Notes	0.5173	0.3590	0.4347	0.4768
Asset-Backed Certificates	Equipment Trust Notes	0.4069	0.3621	0.3018	0.3315
Premium Income Equity Securities	Equipment Trust Notes	0.3028	0.1990	0.2286	0.2589
Principal Exchange Rate Linked Securities	Equipment Trust Notes	0.2889	0.1692	0.2212	0.2319
Premium Income Equity Securities	Principal Exchange Rate Linked Securities	0.6023	0.5730	0.4012	0.3852
Remarketable Term Income Equity Securities	Principal Exchange Rate Linked Securities	0.4986	0.4391	0.3282	0.3229
Convertible Exchangeable Depositary Preferred	Principal Exchange Rate Linked Securities	0.3831	0.3141	0.2709	0.2774
Aircraft Leasing	Principal Exchange Rate Linked Securities	0.3120	0.1947	0.2054	0.2190
Flexible Money Market Preferred Stock	Principal Exchange Rate Linked Securities	0.2862	0.1868	0.2152	0.2234
Asset-Backed Certificates	Principal Exchange Rate Linked Securities	0.2794	0.1625	0.2169	0.2288
Fuel Financing	Principal Exchange Rate Linked Securities	0.2677	0.1768	0.2139	0.2149
Secure Principal Energy Receipts	Principal Exchange Rate Linked Securities	0.2666	0.1524	0.2191	0.2098
Subordinated Pay-In-Kind Notes	Pay-In-Kind Notes	0.9063	0.8554	0.9189	0.9271
Senior Secured Pay In Kind Debentures	Pay-In-Kind Notes	0.7538	0.6968	0.7809	0.8040
Senior Pay-In-Kind Preferred Stock	Pay-In-Kind Notes	0.6378	0.6597	0.6632	0.7110
Flexible Money Market Preferred Stock	Pay-In-Kind Notes	0.3448	0.2866	0.2462	0.2869
Asset-Backed Certificates	Pay-In-Kind Notes	0.3163	0.1996	0.2382	0.2700
Premium Income Equity Securities	Pay-In-Kind Notes	0.2997	0.2177	0.2299	0.2599
Principal Exchange Rate Linked Securities	Pay-In-Kind Notes	0.2953	0.1915	0.2217	0.2344

C.4 Novelty Index

We define the novelty of product i by comparing it to the products that were created before product i (denoted as Ω_i). For any product created after 1985, we compute:

$$N_i = 1 - \max(\Omega_i), \quad \text{where} \quad \Omega_i = \left\{ s_{ij} \cdot \mathbf{1}_{\{c_j < c_i^*\}} \mid j = 1, 2, \ldots, N \right\}.$$

Here, c_i is the year in which product i first appeared, and $\mathbf{1}_{\{c_j < c_i^*\}}$ is a dummy variable that indicates whether product j was created before product i. The novelty measure N_i is guaranteed to lie in the range $[0, 1]$. Because we compute the difference between one and the maximum similarity, a value of zero indicates that the product is identical to an existing product, while a value of one indicates that the product is completely distinct from any existing product. We compute the novelty measure only for financial products created after 1985, as we lack information on the comparison set for older products.

In practice, implementing our measure involves two considerations regarding the comparison set Ω_i.[26] First, the comparison set consists of products with cohort years older than that of product i, which can be defined for the entire economy or for a specific subset. We define our baseline measure using cohort year information from the product-year dataset covering the entire economy. A key robustness check is to construct the measure using cohort year data specific to the non-financial corporate sector (NF) to match the underlying level of analysis in the main paper. Differences between these measures arise because some products are initially introduced by firms in the financial sector. Second, the comparison set Ω_i includes more elements for products created in more recent cohorts, which can bias the measure downwards. Our baseline adjusts for this effect. We also explored bootstrap adjustments that randomize the set of older products while keeping the number of products fixed. This approach delivers a measure that approximates: $N_i = 1 - \{\max(\Omega_i) - \text{mean}(\Omega_i)\}$.

Table C5 provides a summary of the measures of novelty using similarities from any vectorization model i. Throughout the paper, our baseline measure is Method 1 with bootstrap adjustment and the entire economy as the comparison set (Method 1 Boot). All other methods and comparison sets are used as robustness checks.

[26] In addition to the cohort condition, we also evaluate whether to include only active products or those specific to a particular sector. Alternative measures are available upon request.

Table C5: Novelty Index

Name	Formula	Similarity method	Conditions on Counterpart Older	Still Active	SIC	Sector
Method i	$1 - \max(\Omega_i)$	Model i	yes	no	no	ALL
Method i NF	$1 - \max(\Omega_i)$	Model i	yes	no	no	NF
Method i Boot	$1 - \{\max(\Omega_i) - \text{mean}(\Omega_i)\}$	Model i	yes	no	no	ALL
Method i Boot NF	$1 - \{\max(\Omega_i) - \text{mean}(\Omega_i)\}$	Model i	yes	no	no	NF

Notes: The table provides a description of the alternative versions for any vectorization method i.

Table C6 provides descriptive statistics for the baseline and robustness measures for Model 1.[27] The measures differ in levels but are highly correlated. The average novelty for our baseline option is 0.249, which is lower than the measure obtained when using the non-financial sector as the comparison set, but higher than the measures without bootstrap adjustment. The use of the entire economy versus the non-financial sector as the comparison set affects the level by less than 0.05 but produces measures that are only about 0.75 correlated. In contrast, the bootstrap adjustment impacts the level by approximately 0.15, while producing measures that remain highly correlated (above 0.92).

Table C6: Statistics on Similarity Scores

	Mean	Std.Dev.	Correlations Method 1	Method1 NF	Method 1 Boot	Method 1 Boot NF
Method 1	0.105	0.133	1			
Method 1 NF	0.150	0.140	0.792	1		
Method 1 Boot	0.249	0.133	0.926	0.695	1	
Method 1 Boot NF	0.297	0.136	0.744	0.925	0.794	1

Notes: The table provides statistics about novelty index for 621 observations.

To further evaluate the differences across methods, Table C7 provides the novelty indexes for the securities listed in Table C4 that were created after 1985. The novelty rankings are very similar across all four methods. The security with the largest difference across methods is *Equipment Note Pass-Through Certificates*, as the closest older product, *Pass-Through Certificates*, was primarily used by the financial sector. In contrast, *Flexible Auction Preferred Shares* have very low novelty because similar products were already available in the market. Finally, *Principal Exchange Rate Linked Securities* exhibit high novelty since

[27]Equivalent statistics are available for all other vectorization methods defined above. Differences across vectorization methods have a smaller impact on the novelty measures.

no comparable products were available when they were first created (the closest being *Global Notes*).

Table C7: Examples Novelty

	Method 1	Method1 NF	Method 1 Boot	Method 1 Boot NF
Flexible Auction Preferred Shares	0.00	0.00	0.07	0.07
Asset-Backed Certificates	0.00	0.13	0.11	0.24
Auction Rate Notes	0.00	0.22	0.14	0.36
Premium Income Equity Securities PIES	0.08	0.15	0.14	0.20
Pay-In-Kind Notes	0.00	0.11	0.16	0.26
Equipment Lease Notes	0.05	0.05	0.17	0.17
Pay-In-Kind Preferred Stock	0.02	0.03	0.18	0.20
Senior Pay-In-Kind Preferred Stock	0.00	0.01	0.18	0.21
Equipment Note Pass-Through Certificates	0.00	0.34	0.19	0.52
Subordinated Pay-In-Kind Notes	0.00	0.08	0.20	0.28
Mortgage-Backed Notes	0.00	0.00	0.20	0.19
Flexible Money Market Preferred Stock	0.06	0.06	0.22	0.24
Equipment Trust Notes	0.04	0.04	0.23	0.23
Senior Secured Pay In Kind Debentures	0.14	0.14	0.32	0.32
Remarketable Term Income Equity Securities	0.23	0.23	0.33	0.33
Guaranteed Equip Trust Certs	0.24	0.24	0.34	0.34
Convertible Auction Preferred	0.27	0.27	0.37	0.38
Secure Principal Energy Receipts	0.29	0.29	0.39	0.39
Auction Rate Debentures	0.27	0.27	0.40	0.39
Principal Exchange Rate Linked Securities	0.76	0.76	0.78	0.78

Internet Appendix

D Derivations of Analytical Results

Proof of Lemma 1

An investor n in security type i chooses the quantity of each financial product to trade in order to maximize her utility (4). Substituting C^n in the utility function we obtain

$$V^n = \zeta^n \sum_{i,\ell} q_{i\ell}^n E\left(W_{i\ell}\right) - \frac{\gamma}{2}\left(\mathbf{q}^n\right)^T \mathcal{V}_W \mathbf{q}^n - \sum_{i,\ell} p_{i\ell} q_{i\ell}^n,$$

where $\mathbf{q}^n$ is a column vector of the quantities of products $W_{i\ell}$ that investor n acquires, and $\mathcal{V}_W$ is the variance covariance matrix of the products in investor n's portfolio. Note that under our assumptions the matrix $\mathcal{V}_W$ is a block-diagonal matrix, so that on the diagonal each block represents the variance-covatiance matrix of financial products within a sector, while elements off-diagonal are 0.

Then, we can derive the optimal quantity for each financial product that an investor n chooses to acquire sector by sector. Thus, for each sector s in which the investor $n \in \eta_{is}$ trades financial products $W_{i\ell}$ with $\ell \in L_s$, the first order condition for each financial product implies that

$$\zeta^n E\left(\mathbf{W}_{is}\right) - \gamma \mathcal{V}_{W_s} \mathbf{q}_{is}^n - \mathbf{p}_{is} = 0, \forall n \in \eta_{is} \tag{D.1}$$

where $\mathbf{W}_{is} = \left(W_{i\ell}\right)_{\ell \in L_{is}}$ is the vector of financial products payoffs that investor n trades in sector s, $\mathbf{q}_{is}^n = \left(q_{i\ell}^n\right)_{\ell \in L_{is}}$ is a column vector of the quantities of products $W_{i\ell}$ that investor n acquires in sector s, and $\mathbf{p}_{is} = \left(p_{i\ell}\right)_{\ell \in L_{is}}$ is the vector of prices of financial products payoffs that investor n trades in sector s. From (D.1) it follows that

$$\mathbf{q}_{is}^n = \frac{1}{\gamma} \mathcal{V}_{W_{is}}^{-1}\left(\zeta^n E\left(\mathbf{W}_{is}\right) - \mathbf{p}_{is}\right).$$

The price for each financial product must be such that the market for the financial product $W_{i\ell}$ clears

$$\int q_{i\ell}^n dn = a_{i\ell}, \forall \ell \in L_{is}.$$

Substituting the optimal demands of investors into the market clearing conditions we obtain

$$\frac{1}{\gamma} \eta_{is} \mathcal{V}_{W_{is}}^{-1}\left(\mu_\zeta E\left(\mathbf{W}_{is}\right) - \mathbf{p}_{is}\right) = \mathbf{a}_{is},$$

where $\mathbf{a}_{is} = (a_{i\ell})_{\ell \in L_{is}}$ represents a column vector of the quantities supplied by each issuer $\ell \in L_{is}$.

Thus, it follows that

$$\mathbf{p}_{is} = \mu_{\zeta} E\left(\mathbf{W}_{is}\right) - \frac{\gamma}{\eta_{is}} \mathcal{V}_{W_{is}} \mathbf{a}_{is}. \tag{D.2}$$

where the matrix $\mathcal{V}_{W_{is}}$ has $z_{is}^2 \left(\sigma_s^2 + \sigma_{\varepsilon_s}^2\right)$ on the diagonal and $z_{is}^2 \sigma_s^2$ off diagonal.

Proof of Proposition 1

Each issuer $\ell \in L_{is}$ choose a quantity $a_{i\ell}$ to maximize her payoff (3). The FOC for an issuer $\ell \in L_{is}$ is

$$E\left(p_{i\ell} - W_{i\ell}\right) + \frac{\partial p_{i\ell}}{\partial a_{i\ell}} a_{i\ell} = 0$$

or

$$E\left(p_{i\ell} - W_{i\ell}\right) = \frac{\gamma}{\eta_{is}} z_{is}^2 \left(\sigma_s^2 + \sigma_{\varepsilon_s}^2\right) a_{i\ell}.$$

Substituting the price $p_{i\ell}$ given by (5), we obtain

$$\left(\left(\mu_{\zeta} - 1\right) E\left(W_{i\ell}\right) - \frac{\gamma}{\eta_{is}} z_{is}^2 \left(\left(\sigma_s^2 + \sigma_{\varepsilon_s}^2\right) a_{i\ell} + \sum_{\substack{\ell' \in L_{is} \\ \ell' \neq \ell}} \sigma_s^2 a_{i\ell'} \right) \right) - \frac{\gamma}{\eta_{is}} z_{is}^2 \left(\sigma_s^2 + \sigma_{\varepsilon_s}^2\right) a_{i\ell} = 0.$$

Aggregating for all $\ell \in L_{is}$ we can solve for

$$\sum_{\ell \in L_{is}} a_{i\ell} = \frac{\eta_{is}\left(\mu_{\zeta} - 1\right)}{\gamma} \frac{1}{z_{is}^2 \left(\sigma_s^2 + 2\sigma_{\varepsilon_s}^2 + \sigma_s^2 L_{is}\right)} \left[\sum_{\ell \in L_{is}} E\left(W_{i\ell}\right) \right],$$

and using that $E\left(W_{i\ell}\right) = x_{is}$ we obtain that

$$a_{i\ell} = \frac{x_{is}}{z_{is}^2} \frac{1}{\left(\sigma_s^2 + 2\sigma_{\varepsilon_s}^2 + L_{is}\sigma_s^2\right)} \frac{\left(\mu_{\zeta} - 1\right)\eta_{is}}{\gamma}.$$

Substituting the quantities back in the price $p_{i\ell}$ given by (5) we obtain

$$p_{i\ell} = \frac{x_{is}}{\sigma_s^2 + 2\sigma_{\varepsilon_s}^2 + \sigma_s^2 L_{is}} \left(\sigma_{\varepsilon_s}^2 + \sigma_s^2 L_{is} + \mu_{\zeta}\sigma_s^2 + \mu_{\zeta}\sigma_{\varepsilon_s}^2\right)$$

which gives us the Lerner index of firm ℓ in product i, defined in Equation (7), as

$$\Lambda_{i\ell} = (\mu_\zeta - 1) \frac{1}{(L_{is} - 1) \frac{\sigma_s^2}{\left(\sigma_s^2 + \sigma_{\varepsilon_s}^2\right)} + 1 + \mu_\zeta} \tag{D.3}$$

Thus, we can re-write the quantity of product i that firm ℓ issues as

$$a_{i\ell} = \frac{x_{is}}{z_{is}^2} \frac{1}{\sigma_s^2 + \sigma_{\varepsilon_s}^2} \frac{\Lambda_{i\ell}}{1 - \Lambda_{i\ell}} \frac{\eta_s}{\gamma}.$$

Proof of Proposition 2

Condition 2 in Definition 1 implies that a set of security types, $I_s \subset \mathcal{I}_s$, in sector s and a distribution of issuers $\{L_{is}\}_{i \in I_s}$ over security types is supported in equilibrium if no issuer has an incentive to exit a security and enter another security. In other words, for any two financial products $i\ell$ and $i'\ell$ it must be that

$$E\left(p_{i\ell} - W_{i\ell}\right) \times a_{i\ell} \geq E\left(p_{i'\ell} - W_{i'\ell}\right) \times a_{i'\ell} \text{ for any } \ell \in L_{is}$$

and, at the same time

$$E\left(p_{i\ell'} - W_{i\ell'}\right) \times a_{i\ell'} \leq E\left(p_{i'\ell'} - W_{i'\ell'}\right) \times a_{i'\ell'} \text{ for any } \ell' \in L_{i's}.$$

Using (10), the equilibrium conditions become

$$\frac{\gamma}{\eta_{is}} z_{is}^2 \left(\sigma_s^2 + \sigma_{\varepsilon_s}^2\right) a_{i\ell} \times a_{i\ell} \geq \frac{\gamma}{\eta_{is}} z_{i's}^2 \left(\sigma_s^2 + \sigma_{\varepsilon_s}^2\right) a_{i'\ell} \times a_{i'\ell} \text{ for any } \ell \in L_{is}$$

and

$$\frac{\gamma}{\eta_{is}} z_{is}^2 \left(\sigma_s^2 + \sigma_{\varepsilon_s}^2\right) a_{i\ell'} \times a_{i\ell'} \leq \frac{\gamma}{\eta_{is}} z_{i's}^2 \left(\sigma_s^2 + \sigma_{\varepsilon_s}^2\right) a_{i'\ell'} \times a_{i'\ell'} \text{ for any } \ell' \in L_{i's},$$

or, equivalently,

$$z_{is} a_{i\ell} \geq z_{i's} a_{i'\ell}$$

and

$$z_{is} a_{i\ell'} \leq z_{i's} a_{i'\ell'}.$$

Since we assume that $\eta_{is} = \eta_{i's} = \eta_s$ for any securities i, $i' \in \mathcal{I}_s$, if we substitute the quantities $a_{i\ell}$ from (8), we obtain that the equilibrium conditions are

$$\chi_{is}\left[\frac{1}{\left(\sigma_s^2+2\sigma_{\varepsilon_s}^2+L_{is}\sigma_s^2\right)}\right]\geq\chi_{i's}\left[\frac{1}{\left(\sigma_s^2+2\sigma_{\varepsilon_s}^2+\left(L_{i's}+1\right)\sigma_s^2\right)}\right],$$

and

$$\chi_{is}\left[\frac{1}{\left(\sigma_s^2+2\sigma_{\varepsilon_s}^2+\left(L_{is}+1\right)\sigma_s^2\right)}\right]\leq\chi_{i'}\left[\frac{1}{\left(\sigma_s^2+2\sigma_{\varepsilon_s}^2+L_{i's}\sigma_s^2\right)}\right].$$

A sufficient condition for the equilibrium is then

$$\chi_{is}\frac{1}{\sigma_s^2+2\sigma_{\varepsilon_s}^2+L_{is}\sigma_s^2}=\chi_{i's}\frac{1}{\sigma_s^2+2\sigma_{\varepsilon_s}^2+L_{i's}\sigma_s^2} \tag{D.4}$$

or

$$\chi_{is}\frac{\Lambda_{i\ell}}{(1-\Lambda_{i\ell})}=\chi_{i's}\frac{\Lambda_{i'\ell}}{(1-\Lambda_{i'\ell})}$$

Proof of Corollary 1

Part 1

Making use of condition (D.4) that we derived in the proof of Proposition 2 and summing up for all $i\in I_s$, we obtain that

$$\frac{\chi_{is}}{\sigma_s^2+2\sigma_{\varepsilon_s}^2+L_{is}\sigma_s^2}=\frac{1}{\left(\sigma_s^2+2\sigma_{\varepsilon_s}^2+\frac{L_s}{I_s}\sigma_s^2\right)}\frac{\sum\limits_{i'\in I_s}\chi_{i's}}{I_s}. \tag{D.5}$$

Equation (D.5) holds for all products i, including the product that is issued with the lowest productivity χ_{is}^{min}. However, by construction, if a product is issued it must have at least one issuer, or $L_{is}\geq 1$. Then, Equation (D.5) implies that

$$\chi_{is}^{min}\geq\frac{2\sigma_s^2+2\sigma_{\varepsilon_s}^2}{\left(\sigma_s^2+2\sigma_{\varepsilon_s}^2+\frac{L_s}{I_s}\sigma_s^2\right)}\frac{\sum\limits_{i'\in I_s}\chi_{i's}}{I_s}.$$

Using that $\rho_s=\sigma_s^2/\left(\sigma_s^2+\sigma_{\varepsilon_s}^2\right)$ we obtain inequality (12).

Part 2

If condition (D.4) holds, this follows immediately.

Derivations of Total Proceeds in Sector s in Equation (13)

To obtain the total proceeds in (13) we first obtain the proceeds that each firm in sector s receives. We start by substituting the expressions for $a_{i\ell}$ given by (8) and $p_{i\ell}$ given by (5) to obtain

$$E\left(p_{i\ell}\right) \times a_{i\ell} = \chi_{is}^2 \frac{1}{\left(\sigma_s^2+\sigma_{\varepsilon_s}^2\right)} \frac{\Lambda_{i\ell}}{\left(1-\Lambda_{i\ell}\right)^2} \frac{\eta_s}{\gamma}. \tag{D.6}$$

Using that Equation (D.3) implies that $\Lambda_{i\ell} = \Lambda_{i\ell'} = \Lambda_i$ for any ℓ and $\ell' \in L_{is}$ and summing up for all firms that issue product i in sector s, we obtain

$$\sum_{\ell \in L_{is}} E\left(p_{i\ell}\right) \times a_{i\ell} = L_{is} \left(\chi_{is}^2 \frac{1}{\left(\sigma_s^2+\sigma_{\varepsilon_s}^2\right)} \frac{\Lambda_i}{\left(1-\Lambda_i\right)^2} \frac{\eta_s}{\gamma} \right),$$

or

$$\sum_{\ell \in L_{is}} E\left(p_{i\ell}\right) \times a_{i\ell} = L_{is} \left(\chi_{is} \frac{\Lambda_i}{1-\Lambda_i} \right)^2 \frac{1}{\left(\sigma_s^2+\sigma_{\varepsilon_s}^2\right)} \frac{1}{\Lambda_i} \frac{\eta_s}{\gamma}. \tag{D.7}$$

Making use of the equilibrium condition (11) and summing up for all $i \in I_s$, we obtain that

$$\chi_{is} \frac{\Lambda_i}{\left(1-\Lambda_i\right)} = \frac{\frac{1}{I_s} \sum\limits_{i' \in I_s} \chi_{i's}}{\frac{1}{I_s} \sum\limits_{i' \in I_s} \frac{\left(1-\Lambda_{i'}\right)}{\Lambda_{i'}}} \tag{D.8}$$

Substituting (D.8) into (D.7) and summing up for all product types i issued in sector s, we obtain

$$\sum_{i \in I_s} \sum_{\ell \in L_{is}} E\left(p_{i\ell}\right) \times a_{i\ell} = \frac{\eta_s}{\gamma} \left(\frac{\sum\limits_{i' \in I_s} \chi_{i's}}{I_s} \right)^2 \frac{1}{\sigma_s^2+\sigma_{\varepsilon_s}^2} \frac{\sum\limits_{i \in I_s} \frac{L_{is}}{\Lambda_i}}{\left(\frac{1}{I_s} \sum\limits_{i' \in I_s} \frac{\left(1-\Lambda_{i'}\right)}{\Lambda_{i'}} \right)^2} \tag{D.9}$$

Let ω_i represent the market share of proceeds that product i generates in sector s defined as

$$\omega_i = \frac{\sum\limits_{\ell \in L_{is}} E\left(p_{i\ell}\right) a_{i\ell}}{\sum\limits_{i \in I_s} \sum\limits_{\ell \in L_{is}} E\left(p_{i\ell}\right) a_{i\ell}}. \tag{D.10}$$

Substituting the expression of proceeds associated with product i in Equation (D.7) we obtain

$$\omega_i = \frac{L_{is}\frac{1}{(1-\Lambda_i)}\frac{(1-\Lambda_i)}{\Lambda_i}\frac{\eta_s}{\gamma}\left(\chi_{is}\frac{\Lambda_i}{(1-\Lambda_i)}\right)^2\frac{1}{\sigma_s^2+\sigma_{\varepsilon_s}^2}}{\sum\limits_{i\in I_s} L_{is}\frac{1}{(1-\Lambda_i)}\frac{1-\Lambda_i}{\Lambda_i}\frac{\eta_s}{\gamma}\left(\chi_{is}\frac{\Lambda_i}{(1-\Lambda_i)}\right)^2\frac{1}{\sigma_s^2+\sigma_{\varepsilon_s}^2}}$$

$$= \frac{L_{is}\frac{1}{(1-\Lambda_i)}\frac{(1-\Lambda_i)}{\Lambda_i}\frac{\eta_s}{\gamma}\left(\chi_{is}\frac{\Lambda_i}{(1-\Lambda_i)}\right)^2\frac{1}{\sigma_s^2+\sigma_{\varepsilon_s}^2}}{\frac{\eta_s}{\gamma}\left(\chi_{is}\frac{\Lambda_i}{(1-\Lambda_i)}\right)^2\frac{1}{\sigma_s^2+\sigma_{\varepsilon_s}^2}\sum\limits_{i\in I_s} L_{is}\frac{1}{(1-\Lambda_i)}\frac{1-\Lambda_i}{\Lambda_i}}$$

which yields

$$\omega_i = \frac{\frac{L_{is}}{\Lambda_i}}{\sum\limits_{i\in I_s}\frac{L_{is}}{\Lambda_i}}. \tag{D.11}$$

Re-arranging the terms, we have that

$$\frac{\omega_i}{L_{is}}\sum_{i\in I_s}\frac{L_{is}}{\Lambda_i} = \frac{1}{\Lambda_i}.$$

Summing up for all product types i we obtain

$$\left(\sum_{i\in I_s}\frac{\omega_i}{L_{is}}\right)\left(\sum_{i\in I_s}\frac{L_{is}}{\Lambda_i}\right) = \sum_{i\in I_s}\frac{1}{\Lambda_i},$$

and subtracting I_s in both sides it follows that

$$\left(\sum_{i\in I_s}\frac{L_{is}}{\Lambda_i}\right)\left(\sum_{i\in I_s}\frac{\omega_i}{L_{is}}\right) - \sum_{i\in I_s}1 = \sum_{i\in I_s}\frac{1}{\Lambda_i} - \sum_{i\in I_s}1,$$

or

$$\left(\sum_{i\in I_s}\frac{L_{is}}{\Lambda_i}\right)\left[\sum_{i\in I_s}\left(\frac{\omega_i}{L_{is}} - \frac{1}{\sum\limits_{i\in I_s}\frac{L_{is}}{\Lambda_i}}\right)\right] = \sum_{i\in I_s}\left(\frac{1}{\Lambda_i}-1\right).$$

Using again (D.11), it is straightforward to see that this last equation becomes

$$\left(\sum_{i\in I_s}\frac{L_{is}}{\Lambda_i}\right)\left[\sum_{i\in I_s}\left(\frac{\omega_i}{L_{is}} - \frac{\omega_i}{L_{is}}\frac{1}{\Lambda_i}\right)\right] = \sum_{i\in I_s}\left(\frac{1}{\Lambda_i}-1\right).$$

We can now substitute the denominator in Equation (D.9) to obtain total proceeds in sector s as

$$\sum_{i\in I_s}\sum_{\ell\in L_{is}} E\left(p_{i\ell}\right) a_{i\ell} = \frac{\eta_s}{\gamma}\left(\frac{\sum\limits_{i'\in I_s}\chi_{i's}}{I_s}\right)^2 \frac{1}{\sigma_s^2+\sigma_{\varepsilon_s}^2} \frac{\frac{I_s}{\left(\sum\limits_i \frac{L_{is}}{\Lambda_i}\right)}}{\frac{1}{I_s}\left(\left[\sum\limits_i \frac{\omega_i}{L_{is}}\left(1-\Lambda_i\right)\right]\right)^2},$$

which can also be written as

$$\sum_{i\in I_s}\sum_{\ell\in L_{is}} E\left(p_{i\ell}\right) a_{i\ell} = \frac{\eta_s}{\gamma}\left(\frac{\sum\limits_{i'\in I_s}\chi_{i's}}{I_s}\right)^2 \frac{1}{\sigma_s^2+\sigma_{\varepsilon_s}^2} \frac{\sum\limits_i \frac{1}{\sum\limits_i \frac{L_{is}}{\Lambda_i}}}{\frac{1}{I_s}\left(\left[\sum\limits_i \frac{\omega_i}{L_{is}}\left(1-\Lambda_i\right)\right]\right)^2}.$$

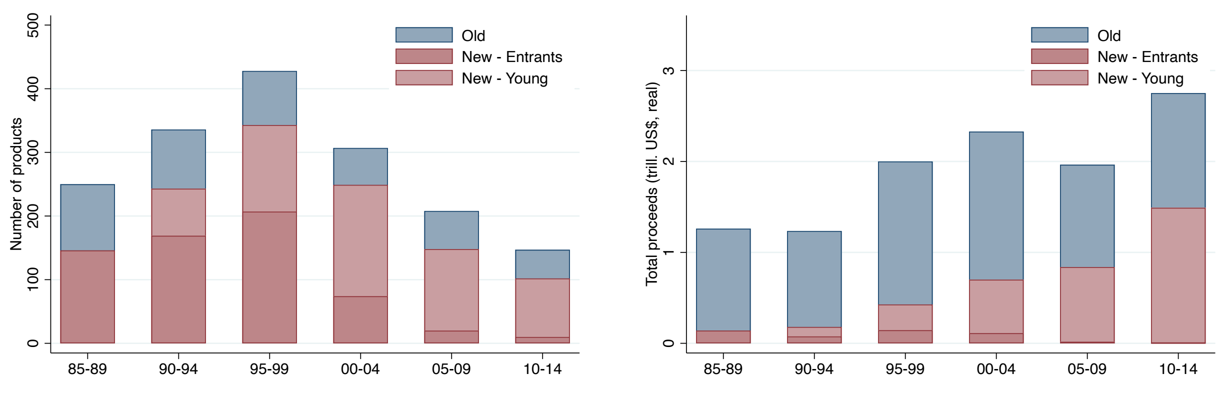
We use (D.11) to derive total proceeds as

$$\sum_{i\in I_s}\sum_{\ell\in L_{is}} E\left(p_{i\ell}\right) a_{i\ell} = \frac{\eta_s}{\gamma}\left(\frac{\sum\limits_{i'\in I_s}\chi_{i's}}{I_s}\right)^2 \frac{1}{\sigma_s^2+\sigma_{\varepsilon_s}^2} \frac{\sum\limits_i \frac{\omega_i}{L_{is}}\Lambda_i}{\frac{1}{I_s}\left(\left[\sum\limits_i \frac{\omega_i}{L_{is}}\left(1-\Lambda_i\right)\right]\right)^2}.$$

Taking logs we obtain the same expression as in Equation (13).

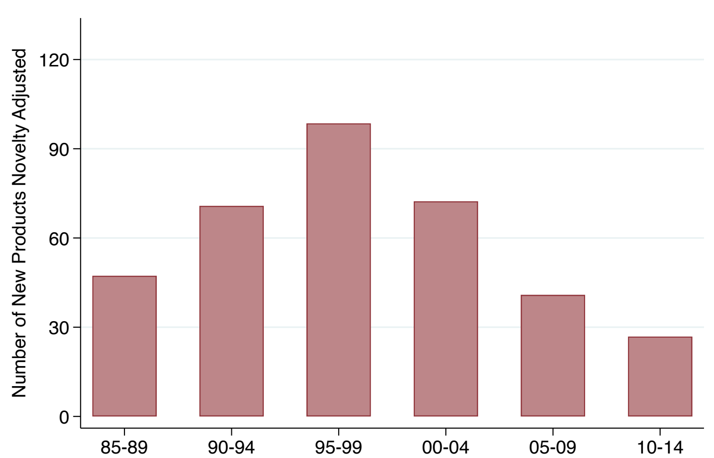
E Supplemental Results: Figures

Figure E1: Evolution and Composition or Products and Proceeds



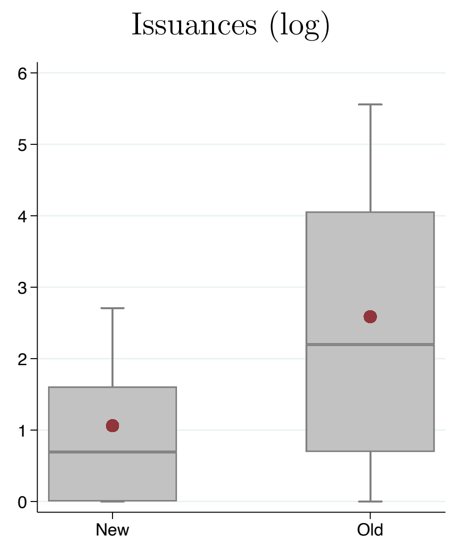
Notes: The figure on the left shows the total distinct financial products from the period 1985-89 to 2010-14. It replicates Figure 2, with the bars being decomposed into three groups of financial products: (i) old are products introduced before 1985, (ii) new-entrants are products introduced in that period, (iii) new-young are products introduced after 1985 but first issued in the preceding periods. The figure on right shows the evolution of total proceeds from the period 1985-89 to 2010-14. The bars are decomposed into the proceeds from issuances of old, new-entrants, and new-young products.

Figure E2: Number of Financial Products Weighted by Novelty



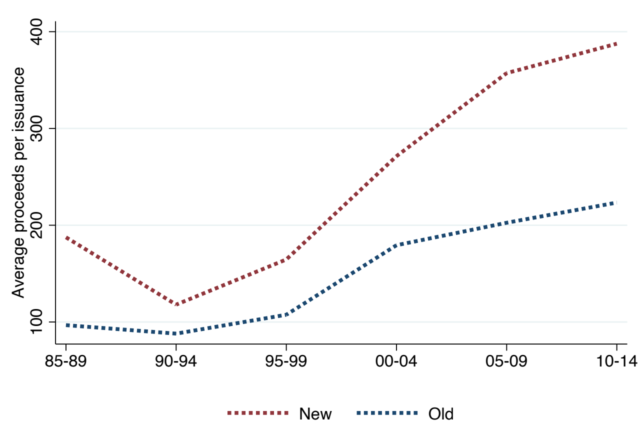
Notes: The figure on the left shows the evolution of total new active types from the period 1985–1989 to 2010-2014, weighted by their novelty. A security type is active if any firm issued a security of that type in that period, and it is new if it was created after 1985. The figure on the right provides the average (line) and p75-p25 range (shadow) of the novelty of new types and new types-sector combination by their period-cohort.

Figure E3: Distribution of Issuances



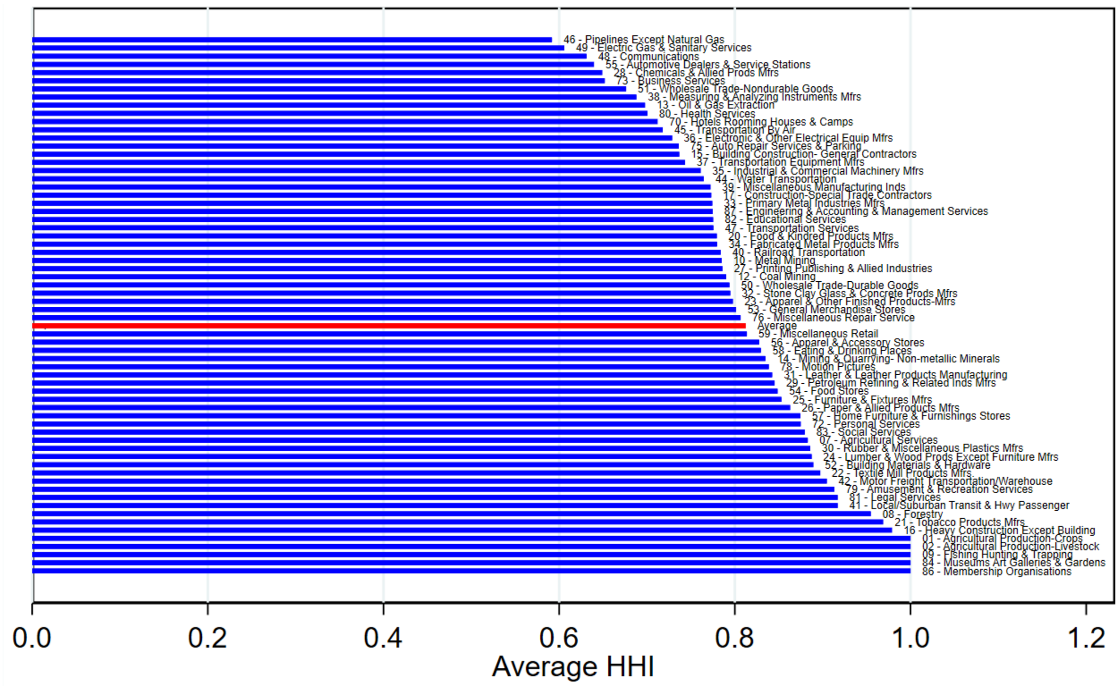
Notes: The figure provides information on the distribution of log issuances for products × period. Statistics for new (introduced after 1985) and old products (introduced before 1985) are provided. For each type of product, we plot five sample statistics - percentile 10, the lower quartile, the median, the upper quartile and the percentile 90 - and the dot indicates the average. We use the baseline data product × period level from period 1985-89 to 2010-14.

Figure E4: Evolution of Proceeds per Issuance



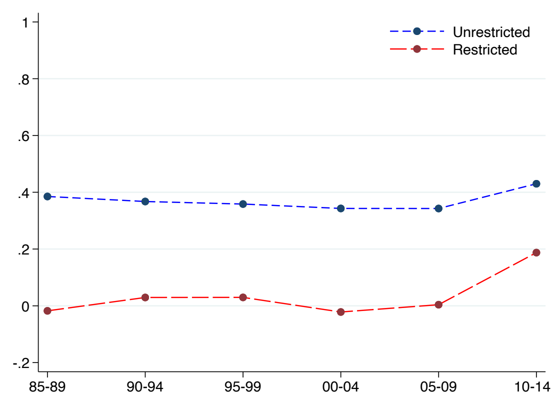
Notes: The figure shows the evolution of proceeds per Issuance over time. New types of securities are securities created after 1985, and old types are security types created before 1985.

Figure E5: Concentration



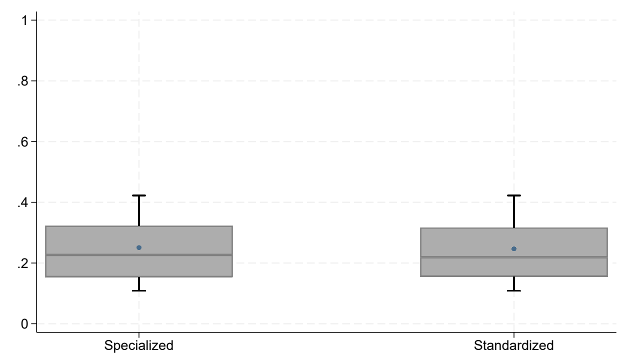
Notes: The figure shows the average HHI per 2-digit sector for the securities within 25th and 75th percentiles of most issued securities in our sample. The average HHI for each sector is computed across security types, where for each type we compute the HHI proceeds concentration index across issuers in the sector.

Figure E6: Rank Correlations



Notes: For each period we show the average of all pairwise rank correlations of 2-digit sectors within product types in terms of proceeds. The unrestricted version computes pairwise correlations including all sectors that issued products in the period. The restricted version instead considers, for each pairwise correlation, only the sectors that issue any of the two products types of the pair.

Figure E7: Distribution of novelty of Specialized and Standardized Products



Notes: The figure compares the distribution of novelty of speciazlied and standardized financial products. Details on the novelty measure are provided in Section 3.1. For each period of entry, we plot five sample statistics - percentile 10, the lower quartile, the median, the upper quartile and the percentile 90 - and dots indicate the averages.

F Supplemental Results: Tables

Table F1: Descriptive Statistics for Sectors

	Obs	Mean	St.Dev.	P25	P50	P75	P90
Sectors							
Proceeds	847	13,628	51,883	368	1,720	7,109	25,183
Issuances	847	85	271	6	19	55	181
Issuer firms	847	54	149	5	15	39	119
Active products	847	14	20	4	8	17	32

Notes: The table provides various descriptive statistics for sectors (defined by 4-digit SIC codes): total proceeds, number of issuances and number if issuer firms, as well as number of products used over the sample period. Proceeds are measured in millions US$ (real), while issuances, issuers, and products refer to simple quantities.

Table F2: Statistics on Components: Robustness

	Mean	Std.Dev.	Correlations $\Delta^{s,t}\Delta Y_{st}$	$\Delta^{s,t}\Delta\bar{\chi}_{st}$	$\Delta^{s,t}\Delta Z_{st}$	$\Delta^{s,t}\Delta L_{st}$	$\Delta^{s,t}\Delta I_{st}$
$\Delta^{s,t}\Delta Y_{st} = \Delta^{s,t}\Delta\bar{\chi}_{st} + \Delta^{s,t}\Delta Z_{st}$	0.00	1.20	1				
Average productivity $\Delta^{s,t}\Delta\bar{\chi}_{st}$	0.00	1.06	0.73	1			
Competition & risk $\Delta^{s,t}\Delta Z_{st}$	0.00	0.83	0.51	-0.21	1		
Number Issuers $\Delta^{s,t}\Delta L_{st}$	0.00	15.61	0.20	0.03	0.24	1	
Number Products $\Delta^{s,t}\Delta I_{st}$	0.00	3.59	0.37	0.07	0.45	0.57	1

Notes: The table provides statistics about (log) proceeds, the components of average productivity and risk and dispersion (as described in Proposition 3), number of issuers, and number of financial products. The first and second columns show the average and standard deviation, respectively. The remaining columns display pairwise correlation coefficients. We use the sector $\times$ period dataset, and for all variables we apply the double-difference operator for sector and period. Sectors are defined with 4-digit SIC codes.

Table F3: Variance Decomposition: Robustness

	Alternative μ_ζ 2	4	6	8	10	12	14	16	18	20
Average productivity	0.6691	0.6695	0.6697	0.6698	0.6699	0.6699	0.6699	0.6700	0.6700	0.6700
Competition and risk	0.3309	0.3305	0.3303	0.3302	0.3301	0.3301	0.3301	0.3300	0.3300	0.3300

Notes: The table presents the results from our decomposition of the (log) proceeds at the sector $\times$ period level, as defined in equation (3). The regressions use the baseline sector $\times$ period dataset with sectors defined by 4-digit SIC codes. We apply the double difference operator for sector and period.

Table F4: Descriptive Statistics

	Obs	Mean	St.Dev.	P25	P50	P75	P90
New-entrant products							
Log new	3,674	0.573	0.720	0	0	1.099	1.609
Share new	3,674	0.174	0.275	0	0	0.254	0.612
Share novelty-adj	3,671	0.042	0.076	0	0	0.056	0.133
Log new specialized	3,674	0.114	0.344	0	0	0	0.693
Log new standardized	3,674	0.525	0.677	0	0	0.693	1.386
Share new specialized	3,674	0.015	0.083	0	0	0	0.010
Share new standardized	3,674	0.159	0.266	0	0	0.214	0.568
Share novelty-adj specialized	3,671	0.004	0.023	0	0	0	0.002
Share novelty-adj standardized	3,671	0.038	0.090	0	0	0.046	0.125
Sector's new-entrant products							
Log sector-new	3,674	1.496	0.745	0.693	1.386	1.946	2.565
Share sector-new	3,671	0.916	0.197	0.968	1	1	1
Share sector-new novelty-adj	2,065	0.173	0.146	0.053	0.155	0.261	0.350
Log sector-new specialized	3,674	0.121	0.356	0	0	0	0.693
Log sector-new standardized	3,674	1.475	0.730	0.693	1.386	1.946	2.485
Share sector-new specialized	3,671	0.016	0.086	0	0	0	0.014
Share sector-new standardized	3,671	0.900	0.214	0.918	1	1	1
Share sector-new novelty-adj specialized	2,065	0.019	0.065	0	0	0	0.044
Share sector-new novelty-adj standardized	2,065	0.155	0.146	0.021	0.133	0.244	0.327

Notes: The table provides various descriptive statistics of the variables used in the paper. The statistics are computed by pooling data over the period 1985–1989 to 2010–2014.

Table F5: New Financial Products and Average Productivity: Robustness for Different Measures of Novelty

	M1	M2	M3	M1	M2	M3	M1	M2	M3	M1	M2	M3
	-	-	-	boot	boot	boot	-	-	-	boot	boot	boot
	-	-	-	-	-	-	NF	NF	NF	NF	NF	NF
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Coefficient	-0.174	-0.288	-0.208	0.982***	0.760***	0.704***	0.754***	0.240	0.490**	1.212***	1.015***	0.938***
	(0.304)	(0.282)	(0.257)	(0.254)	(0.267)	(0.229)	(0.269)	(0.270)	(0.228)	(0.211)	(0.243)	(0.191)
Observations	3,637	3,637	3,637	3,634	3,634	3,634	3,637	3,637	3,637	3,634	3,634	3,634
R-squared	0.202	0.203	0.203	0.207	0.205	0.205	0.205	0.203	0.204	0.212	0.208	0.210
Sector	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: The table presents the regression output from the equation $D_{s,t} = \beta X_{s,t} + \text{Controls}_{s,t} + \alpha_s + \gamma_t + \varepsilon_{s,t}$. The dependent variable is the double difference in productivity $\Delta^{s,t}\bar{\chi}$. The independent variables are the share of novelty-adjusted new entrant products (weighted) using different methods. The regressions include number of issuances (log) as controls. The regressions are based on the baseline sector-period dataset, with sectors classified by 4-digit SIC codes.

Table F6: New Financial Products and Average Productivity: no Controls

Panel A - New-Entrant Products

Dep. Var.	$\Delta^{s,t}\bar{\chi}$			$\Delta^{s,t}\Delta\bar{\chi}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Ind. Var.	log new	share new	share nov-adj	log new	share new	share nov-adj
Coefficient	0.340***	0.545***	1.324***	0.151***	0.355***	1.030***
	(0.039)	(0.075)	(0.266)	(0.041)	(0.085)	(0.298)
Observations	3,637	3,637	3,634	2,598	2,598	2,595
R-squared	0.139	0.132	0.125	0.044	0.046	0.044
Sector	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y
Controls	N	N	N	N	N	N

Panel B - Sector's New-Entrant Products

Dep. Var.	$\Delta^{s,t}\bar{\chi}$			$\Delta^{s,t}\Delta\bar{\chi}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Ind. Var.	log new	share new	share nov-adj	log new	share new	share nov-adj
Coefficient	0.601***	0.959***	0.583***	0.381***	0.787***	0.387
	(0.043)	(0.122)	(0.192)	(0.051)	(0.136)	(0.248)
Observations	3,637	3,635	2,053	2,598	2,595	1,246
R-squared	0.172	0.136	0.291	0.065	0.055	0.220
Sector	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y
Controls	N	N	N	N	N	N

Notes: The table presents the regression output from the equation $D_{s,t} = \beta X_{s,t} + \alpha s + \gamma_t + \varepsilon_{s,t}$. The dependent variable is the double difference in productivity $\Delta^{s,t}\bar{\chi}$ in columns (1) to (3), and the double difference in first differences of the productivity component $\Delta^{s,t}\Delta\bar{\chi}$ in columns (4) to (6). Each column's data results from running the regression on different independent variables defined at the sector-period level: Columns (1) and (4) use the log of the number of new products introduced in the contemporaneous 5-year period, Columns (2) and (5) use the share of new entrant products, Columns (3) and (6) use the share of novelty-adjusted new entrant products. The independent variables are computed weighting by proceeds of the different products in a particular sector-period. In Panel A, new-entrant products are defined across any sector, while in Panel B, new products are defined as new-entrant products within a specific sector. The regressions are based on the baseline sector-period dataset, with sectors classified by 4-digit SIC codes.

Table F7: New Financial Products and Average Productivity: Non-Weighted Independent Variables

Panel A - New-Entrant Products

Dep. Var.	$\Delta^{s,t}\bar{\chi}$			$\Delta^{s,t}\Delta\bar{\chi}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Ind. Var.	log new	share new	share nov-adj	log new	share new	share nov-adj
Coefficient	0.074*	0.247***	0.476*	0.072*	0.163*	0.440
	(0.041)	(0.078)	(0.265)	(0.042)	(0.089)	(0.299)
Observations	3,637	3,637	3,634	2,598	2,598	2,595
R-squared	0.203	0.205	0.204	0.072	0.072	0.071
Sector	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y

Panel B - Sector's New-Entrant Products

Dep. Var.	$\Delta^{s,t}\bar{\chi}$			$\Delta^{s,t}\Delta\bar{\chi}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Ind. Var.	log new	share new	share nov-adj	log new	share new	share nov-adj
Coefficient	0.062	0.855***	0.295	0.234***	0.731***	-0.030
	(0.067)	(0.148)	(0.191)	(0.058)	(0.171)	(0.238)
Observations	3,637	3,635	2,053	2,598	2,595	1,246
R-squared	0.203	0.212	0.353	0.078	0.079	0.249
Sector	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y

Notes: The table presents the regression output from the equation $D_{s,t} = \beta X_{s,t} + \text{Controls}_{s,t} + \alpha_s + \gamma_t + \varepsilon_{s,t}$. The dependent variable is the double difference in productivity $\Delta^{s,t}\bar{\chi}$ in columns (1) to (3), and the double difference in first differences of the productivity component $\Delta^{s,t}\Delta\bar{\chi}$ in columns (4) to (6). Each column's data results from running the regression on different independent variables defined at the sector-period level: Columns (1) and (4) use the log of the number of new products introduced in the contemporaneous 5-year period, Columns (2) and (5) use the share of new entrant products, Columns (3) and (6) use the share of novelty-adjusted new entrant products. The independent variables are unweighted. The regressions include number of issuances (log) as controls. In Panel A, new-entrant products are defined across any sector, while in Panel B, new products are defined as new-entrant products within a specific sector. The regressions are based on the baseline sector-period dataset, with sectors classified by 4-digit SIC codes.

Table F8: Specialized and Standardized New Products and Average Productivity: Alternative Definitions of Standardized/Specialized

Panel A - Specialized defined as used by one sector

Dep. Var.	$\Delta^{s,t}\Delta_{\bar{\chi}}$					
	Log new		Share new		Share novelty-adj	
Ind. Var.	specialized	standardized	specialized	standardized	specialized	standardized
	(1)	(2)	(3)	(4)	(5)	(6)
Coefficient	0.157	0.057	1.685***	0.397***	6.314***	0.863***
	(0.105)	(0.042)	(0.431)	(0.072)	(1.783)	(0.256)
Observations	3,637	3,637	3,637	3,637	3,634	3,634
R-squared	0.203	0.203	0.207	0.211	0.206	0.206
Sector	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y

Panel B - Specialized defined as used by ten sectors

Dep. Var.	$\Delta^{s,t}\Delta_{\bar{\chi}}$					
	Log new		Share new		Share novelty-adj	
Ind. Var.	specialized	standardized	specialized	standardized	specialized	standardized
	(1)	(2)	(3)	(4)	(5)	(6)
Coefficient	0.115**	0.007	0.779***	0.328***	3.172***	0.454
	(0.055)	(0.043)	(0.163)	(0.077)	(0.586)	(0.276)
Observations	3,637	3,637	3,637	3,637	3,634	3,634
R-squared	0.204	0.202	0.209	0.207	0.211	0.204
Sector	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y

Notes: The table presents the regression output from estimating the equation $\Delta^{s,t}\bar{\chi} = \beta X_{s,t} + \text{Controls}_{s,t} + \alpha_s + \gamma_t + \varepsilon_{s,t}$. The dependent variable is the double difference of the productivity component. Each column's data results from running the regression on different independent variables ($X_{s,t}$) at the sector-period level. Columns (1) and (2) display the log of the number of new specialized and standardized products, respectively. Columns (3) and (4) show the share of new entrant specialized and standardized products, respectively. Columns (5) and (6) report the share of novelty-adjusted new entrant specialized and standardized products, respectively. In Panel A, specialized products are those used by one sector, while standardized products are used by more than 1 sector. In Panel B, specialized products are those used by up to ten sectors, while standardized products are used by more than ten sectors. The independent variables are computed weighting by proceeds of the different products in a particular sector-period. The regressions include number of issuances (log) as controls. New-entrant products are defined across any sector. The regressions use the baseline sector-period dataset, with sectors classified by 4-digit SIC codes.

Table F9: Specialized and Standardized New Products and Average Productivity: Alternative Dependent Variable

Dep. Var.	$\Delta^{s,t}\Delta\bar{\chi}$					
	Log new		Share new		Share novelty-adj	
Ind. Var.	specialized (1)	standardized (2)	specialized (3)	standardized (4)	specialized (5)	standardized (6)
Coefficient	0.182***	0.030	0.737***	0.265***	2.455***	0.717**
	(0.068)	(0.043)	(0.235)	(0.087)	(0.827)	(0.310)
Observations	2,598	2,598	2,598	2,598	2,595	2,595
R-squared	0.074	0.071	0.075	0.075	0.074	0.072
Sector	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y

Notes: The table presents the regression output from estimating the equation $\Delta^{s,t}\Delta\bar{\chi} = \beta X_{s,t} + \text{Controls}_{s,t} + \alpha_s + \gamma_t + \varepsilon_{s,t}$. The dependent variable is the double difference of the first difference of the productivity component. Each column's data results from running the regression on different independent variables ($X_{s,t}$) at the sector-period level. Columns (1) and (2) display the log of the number of new specialized and standardized products, respectively. Columns (3) and (4) show the share of new entrant specialized and standardized products, respectively. Columns (5) and (6) report the share of novelty-adjusted new entrant specialized and standardized products, respectively. Specialized products are those used by up to 5 sectors, while standardized products are used by more than 5 sectors. The independent variables are computed weighting by proceeds of the different products in a particular sector-period. The regressions include number of issuances (log) as controls. New-entrant products are defined across any sector. The regressions use the baseline sector-period dataset, with sectors classified by 4-digit SIC codes.

Table F10: Specialized and Standardized New Products and Average Productivity: no Controls

Panel A - New-entrant products

Dep. Var.	$\Delta^{s,t}\bar{\chi}$					
	Log new		Share new		Share novelty-adj	
Ind. Var.	specialized	standardized	specialized	standardized	specialized	standardized
	(1)	(2)	(3)	(4)	(5)	(6)
Coefficient	0.337***	0.291***	1.271***	0.437***	4.475***	0.889***
	(0.070)	(0.041)	(0.228)	(0.078)	(0.785)	(0.280)
Observations	3,637	3,637	3,637	3,637	3,634	3,634
R-squared	0.123	0.132	0.125	0.125	0.127	0.120
Sector	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y
Controls	N	N	N	N	N	N

Panel B - Sector's new-entrant products

Dep. Var.	$\Delta^{s,t}\bar{\chi}$					
	Log new		Share new		Share novelty-adj	
Ind. Var.	specialized	standardized	specialized	standardized	specialized	standardized
	(1)	(2)	(3)	(4)	(5)	(6)
Coefficient	0.319***	0.565***	1.268***	0.451***	1.773***	0.067
	(0.068)	(0.044)	(0.224)	(0.109)	(0.356)	(0.186)
Observations	3,637	3,637	3,635	3,635	2,053	2,053
R-squared	0.122	0.165	0.127	0.122	0.298	0.286
Sector	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y
Controls	N	N	N	N	N	N

Notes: The table presents the regression output from estimating the equation $\Delta^{s,t}\bar{\chi} = \beta X_{s,t} + \alpha s + \gamma_t + \varepsilon_{s,t}$. The dependent variable is the double difference in the productivity component. Each column's data results from running the regression on different independent variables ($X_{s,t}$) at the sector-period level. Columns (1) and (2) display the log of the number of new specialized and standardized products, respectively. Columns (3) and (4) show the share of new entrant specialized and standardized products, respectively. Columns (5) and (6) report the share of novelty-adjusted new entrant specialized and standardized products, respectively. Specialized products are those used by up to 5 sectors, while standardized products are used by more than 5 sectors. The independent variables are computed weighting by proceeds of the different products in a particular sector-period. The regressions include number of issuances (log) as controls. In Panel A, new-entrant products are defined across any sector, whereas in Panel B, new products are defined as new-entrant products within a specific sector. The regressions use the baseline sector-period dataset, with sectors classified by 4-digit SIC codes.

Table F11: Specialized and Standardized New Products and Average Productivity: Non-Weighted Independent Variables

Panel A - New-entrant products

Dep. Var.	$\Delta^{s,t}\bar{\chi}$					
	Log new		Share new		Share novelty-adj	
Ind. Var.	specialized	standardized	specialized	standardized	specialized	standardized
	(1)	(2)	(3)	(4)	(5)	(6)
Coefficient	0.140**	0.024	1.095***	0.139*	3.739***	0.047
	(0.067)	(0.042)	(0.237)	(0.082)	(0.777)	(0.279)
Observations	3,637	3,637	3,637	3,637	3,634	3,634
R-squared	0.204	0.202	0.208	0.203	0.209	0.203
Sector	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y

Panel B - Sector's new-entrant products

Dep. Var.	$\Delta^{s,t}\bar{\chi}$					
	Log new		Share new		Share novelty-adj	
Ind. Var.	specialized	standardized	specialized	standardized	specialized	standardized
	(1)	(2)	(3)	(4)	(5)	(6)
Coefficient	0.121*	-0.011	1.045***	0.312**	1.696***	-0.177
	(0.066)	(0.066)	(0.234)	(0.127)	(0.353)	(0.183)
Observations	3,637	3,637	3,635	3,635	2,053	2,053
R-squared	0.203	0.202	0.208	0.204	0.362	0.352
Sector	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y

Notes: The table presents the regression output from estimating the equation $\Delta^{s,t}\bar{\chi} = \beta X_{s,t} + \text{Controls}_{s,t} + \alpha_s + \gamma_t + \varepsilon_{s,t}$. The dependent variable is the double difference in the productivity component. Each column's data results from running the regression on different independent variables ($X_{s,t}$) at the sector-period level. Columns (1) and (2) display the log of the number of new specialized and standardized products, respectively. Columns (3) and (4) show the share of new entrant specialized and standardized products, respectively. Columns (5) and (6) report the share of novelty-adjusted new entrant specialized and standardized products, respectively. Specialized products are those used by up to 5 sectors, while standardized products are used by more than 5 sectors. The independent variables are unweighted. The regressions include number of issuances (log) as controls. In Panel A, new-entrant products are defined across any sector, whereas in Panel B, new products are defined as new-entrant products within a specific sector. The regressions use the baseline sector-period dataset, with sectors classified by 4-digit SIC codes.

Table F12: Specialized and Standardized New Products and Average Productivity: Alternative Specification

Dep. Var.	$\Delta^{s,t}\bar{\chi}$					
Ind. Var.	Share new			Share novelty-adj		
	(1)	(2)	(3)	(4)	(5)	(6)
specialized	1.271***		1.352***	4.475***		4.577***
	(0.228)		(0.227)	(0.785)		(0.784)
standardized		0.437***	0.465***		0.889***	0.951***
		(0.078)	(0.078)		(0.280)	(0.279)
Observations	3,637	3,637	3,637	3,634	3,634	3,634
R-squared	0.125	0.125	0.136	0.127	0.120	0.131
Sector	Y	Y	Y	Y	Y	Y
Time	Y	Y	Y	Y	Y	Y
Controls	N	N	N	N	N	N

Notes: The dependent variable is the double difference of the productivity component. Columns (1) to (3) show the share of new entrant specialized, standardized, and both types of products, respectively. Columns (4) to (6) report the share of novelty-adjusted new entrant specialized, standardized, and both types of products, respectively. Specialized products are those used by up to 5 sectors, while standardized products are used by more than 5 sectors. The independent variables are computed weighting by proceeds of the different products in a particular sector-period. New-entrant products are defined across any sector. The regressions use the baseline sector-period dataset, with sectors classified by 4-digit SIC codes.