The Rise of Specialized Financial Products*

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Abstract

The number of varieties of financial products that firms can use to raise funds from investors has rapidly expanded over the past decades. And yet, many firms issue only a few standard products, such as common stocks and bonds. This paper studies innovation in financial products using a combination of granular data on security issuance and a model of allocation of financial products to firms in specific sectors. We find three key patterns. First, the differential adoption of products 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. Finally, most funds raised from new financial products come from a large number of distinct products that are highly specialized in that only a few firms use them. Our analysis indicates that innovation in financial markets is akin to innovation in consumer markets, which results not just in improvements in the quality of standardized products, but also in increasing varieties in a given market as products become more specialized.

Keywords: innovation; financial products; specialization; love-of-variety; imperfect competition;

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1 Introduction

Firms depend on access to external financing to fund growth and invest in new projects, and frequently issue securities to raise such funds. A plethora of innovations in the past decades has expanded the set of financial products that firms can choose to issue. While it has been long established that firms are not indifferent to their capital structure, the heterogeneity in their security issuance decisions represents a puzzle. Firms in some sectors issue a narrow set of common financial products, such as stocks and bonds, while firms in other sectors issue a large variety of products. A recent literature on innovation in non-financial products has shown that an important mechanism for firms’ growth is the expansion of varieties they offer.\(^1\) Although financial products are distinct, a greater variety of products may enable firms to issue securities that are a better match for their funding needs. This raises the question of whether the surge in new financial products contributes to easing firms’ access to external funds.

This paper studies innovation in financial products using a combination of granular data on security issuance and a parsimonious model of allocation of financial products to firms. We seek to understand the mechanisms through which innovation in financial products contributes to firms ability to obtain funds. When firms decide to raise funds by issuing securities, they must choose which type of financial product to use from a set of available products. Financial products represent distinct technologies that allow a firm to convert its cash flows into a set of cash flows for investors. Some technologies are relatively simple ownership positions via stock or creditor positions via bonds, while others are more-complex and highly specific. Firms use the financial products that provide the most-favorable payoffs given their financing needs, while accounting for investor demand for products, risk, and competitive forces. The introduction of new financial products allows firms to access a broader set of products, and we evaluate whether the expansion in product choice explains firms’ success in raising funds. The main results are that new financial products contribute significantly to the allocation of funding among firms, mostly because the majority of financial innovations generally result in 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 build on the SDC’s categorization of securities to distinguish between financial products. During

\(^1\)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).
the sample period, we observe an ample number of financial products issued by firms across various sectors of the economy. In particular, the number of distinct financial products available to firms to raise funds from investors went from approximately 150 in 1985 to about 800 distinct products in 2014. These include well-established products, such as Common Shares and Global Notes, as well as less recognizable products, such as Sinking Fund Debentures.

Financial products differ greatly in their adoption across firms. Figure 1 shows the allocation of products to sectors. Each dot in the figure 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 electrical 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, suggesting that the allocation of financial products to firms within specific sectors is not random and some products seem to be specialized to the needs of specific sectors.
Interestingly, new financial products, identified based on the timing of each product’s introduction to the market, are those that tend to be specialized. On average, almost 50% of new products are used only by firms within one sector in any period, compared to only 15% for older products. This pattern is particularly relevant because our analysis indicates that new financial products accounted for a large share of all funds raised. We measure the degree to which new products differ from existing products using an original procedure to quantify the degree of novelty of each new financial product. We mine the characteristics of each financial product from articles published by Investopedia by building descriptions of products using natural-language processing methods (Manning, Raghavan and Schütze, 2008). This textual analysis allows us to create systematic measures of similarity in the descriptions between all pairs of products in our sample. Using these measures of pairwise similarity, we then calculate the degree of novelty of any new financial product relative to the closest product already on the market. We find that while innovation is incremental, it is also persistent and new products are identifiably distinct.

We construct a simple conceptual framework that guides our analysis of the allocation of financial products to firms and allows us to use variables we observe in the data. Our framework relies on two main building blocks. First, 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 the 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 (2022) for an extensive survey). To capture the variety of products we observe in the data in a flexible and tractable way, we take a different approach. For our analysis it is sufficient to consider that products are characterized by different levels of productivity. A higher-productivity product improves investors expected utility from holding it, by increasing expected payoff and/or decreasing variance of the payoff. We allow heterogeneity in the productivity of financial products across sectors to accommodate the possibility that financial products may be horizontally differentiated.

Second, issuers of securities are large relative to investors in the model, so firms choose which security to issue strategically, taking other firms’ choices into account. Thus, a firm’s relative market power is endogenous and depends on how many other firms choose to issue the same financial product. Anecdotal evidence supports that firms consider market conditions when issuing securities. For instance, in June 1999 Ford delayed the launch of a multibillion bond issuance to avoid excess supply in the corporate bond markets, in the aftermath of a
several other substantial offerings.\textsuperscript{2}

To sum up, firms prefer to issue higher-productivity security contracts because these contracts are more valuable to investors and generate more proceeds, \textit{ceteris paribus}. However, higher-productivity products also attract more issuers, with the result that each issuer has less market power and ultimately is not able to raise as much external funds. The tension between financial products’ productivity and firms’ market power when issuing those products is central to the model, allowing multiple products of varying productivity to be issued in equilibrium. This way, unlike the traditional channel in which financial innovation is creating value by completing markets through spanning, products in our model are valuable because they create new markets for firms.

We use the framework to tease out the role that the differential adoption of new financial products might play in explaining differences in firms’ ability to raise external funding. 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 market power of competing firms issuing securities and the idiosyncratic volatility of firms. The third component captures various determinants of investor demand. We estimate the relative importance of these margins by following the allocation of products among firms over time. 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 quantify the overall importance of this factor, we use the structure of the model to quantify the importance of a financial product’s 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 market power of firms competing over investors and differences across risk factors. Differences in investor demand across sectors play only a small 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. We establish that new financial products contributed to

\textsuperscript{2}“Ford Credit Puts End to Rumors By Delaying Giant Bond Offering” (WSJ, 1999).
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, innovation in financial products seems to have something important in common with innovation in other products, that a substantial portion of innovative effort focuses on appealing to the preferences of increasingly specific customer segments.

Throughout our analysis, we take firms’ decisions to raise funds via securities contracts as given. We acknowledge, though, that firms can also raise funds by borrowing from banks, and many firms rely on both sources of funding in reality. However, recent evidence suggests that borrowing from banks costs more than borrowing from the market (Schwert, 2019). This finding is consistent with Denis and Mihov (2003), who show that firms with better credit ratings issue more public debt. These findings suggest that firms prefer to issue securities when not otherwise constrained. As such, it is important to understand the role that financial products play in firms’ ability to access funds, even though the less-successful firms in securities markets may substitute security issuances for bank loans.

Related Literature – Our quantitative work on measuring innovation in financial products and our modeling of the margins affecting the choice of which products to use are relevant to the literature on financial innovation, economic growth, and measuring the margins that affect innovation. Despite growing interest in the consequences of financial innovation (Philippon, 2015), quantitative work on the topic has faced challenges, as Frame and White (2004) note.  

The measurement of innovation is a difficult task in any context, and is especially so in the case of financial products (Bryan and Williams, 2021). Traditional measures of innovative activity, such as R&D spending and patenting, remained elusive until very recently (Lerner, Seru, Short and Sun, 2022). Previously, Lerner (2006) developed a measure of financial innovation based on news stories in the Wall Street Journal. We focus on financial innovation in the securities market, where we rely on listings of new securities compiled by the SDC, as

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3Comprehensive surveys are provided by Tufano (2003) and Lerner and Tufano (2011).
suggested in Tufano (2003). We use natural-language processing techniques to develop an
index of novelty that allows us to distinguish the truly innovative innovations identified in
the SDC database from those that are only minor variations on securities contracts already
on the market.

A larger body of work is focused on assessing the impact of financial innovation, and
makes a theme of the deleterious consequences of innovation in the securities market. Allen
(2012) investigates how the introduction of new financial products has been detrimental to
investors, especially in the aftermath of the financial crisis. 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 overall message of this literature is
that investment banks reap the benefits of innovative financial products at the expense of
investors. A different perspective is proposed by Calvet, Célérier, Sodini and Vallée (2021)
who argue that banks introduce innovative product features to tap into investors pools
that otherwise would not participate in financial markets. While the welfare effects and
the social impact of financial innovations are particularly difficult to evaluate (Lerner and
Tufano, 2011), this suggests a positive role of financial innovation. We are also interested
in understanding a potential positive consequence of financial innovation, but we focus on
the benefits that the suppliers, or issuers, of innovative securities contracts might enjoy,
abstracting away from the consequences investors face.

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 mar-
kets (Clark, Houde and Kastl, 2021), competition between firms when creating 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, Ros-
tek 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.4 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 de-

4A 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).
composition 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. Then section 3 establishes our model, and section 4 details the methods and results of our decomposition of the margins behind variation in proceeds from securities. We explain these margins with mechanisms in section 5, and draw conclusions in section 6.

2 Data and Context

We have compiled data for a comprehensive empirical investigation 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 entitles investors to receive a claim to a set of cash-flows. We will refer to the type of contract a firm uses as a “financial product.” 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 three decades, from 1985 until 2014.

2.1 Datasets

We use data from 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 securities with maturities greater than one year (where applicable), starting in 1970. The data include issuances of equity and debt securities, and exclude derivatives (e.g. options and futures). 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. Since the

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coverage improves greatly in the early 1980s,\footnote{The coverage of this dataset has expanded over time, with private placements being included only from 1981, international issuances from 1983, and medium-term notes from 1982. For the purpose of our analysis it is important that we have complete coverage.} we restrict our sample to the period 1985-2014, organized into five-year periods.

For each issuance of a security we observe the date, the name of the issuing firm, other issuer information, and the type of product issued. Importantly, we also observe the amounts of funds raised through in each issuance. 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.\footnote{See Figure 8 in Appendix B.}

The baseline dataset comprises 72,190 issuances by 17,851 issuer firms, across 847 four-digit SIC sectors. Throughout the paper we use sectors as the unit of analysis to capture heterogeneity across firms and overcome the sparsity of the data. 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 indeed, as our periods are five years long. Thus, using issuers as our unit of observation would yield variation from only a few (very large) firms.

\section*{2.2 Varieties of Financial Products}

Financial products admit a great variety, ranging from the relatively simple ownership positions in a corporation through stock or creditor relationships through bond holdings to more complex arrangements. Much of the theoretical and empirical work about the economics of finance considers a highly stylized world in which only a few types of financial products exist, typically just debt and equity. In reality, however, a wide range of financial products are offered (Tufano, 2003). We build on the original SDC data to create a dataset that allows us to study the full variety of financial products. We propose a baseline definition of a new financial product and we develop a measure of a financial product’s degree of novelty relative to existing financial products.

\subsection*{2.2.1 Definition and Measurement}

Our differentiation between financial products follows the SDC’s categorization of types of securities. The SDC distinguishes close to 800 types of securities issued by non-financial corporations in the U.S. over the period 1985-2014. These include the relatively well-known
“Common Shares” and “Bonds”, as well as more-obscure financial products like “Equipment Notes”, “Lease Bonds”, and “Senior Pay-In-Kind Notes”. 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.\(^7\)

We use the panel structure of the SDC data to identify when each financial product was first introduced. We refer to any financial product created after 1985 as “new”, and those that already existed before 1985 as “old”.\(^8\) For each time period, we can identify the set of active financial products, and we can determine the length of time that a new product has been available to issuers. We distinguish between products that were just introduced (“new-entrants”) and products that were introduced in previous periods (“new-young”).\(^9\) For products that are no longer active, we use the product’s exit time to determine the duration of distinct products.

Figure 2 shows the evolution of total proceeds from financial products decomposed into “old”, “new-entrants”, and “new-young”. Two salient patterns emerge. First, the proceeds

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\(^7\)SDC categorizes financial contracts using information from SEC filings, prospectuses, industry news sources, wires, and daily surveys of underwriters and other corporate-finance contacts.

\(^8\)Because we have data starting in 1970, we can judge whether a product issued after 1985 was already available on the market.

\(^9\)For old financial products, we cannot always determine the first year in the dataset, and as such cannot determine the exact age of that type of contract.
Figure 3: Financial Products: Evolution and Composition

Notes: The figure shows the evolution of total distinct financial products 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. The bars decompose products into three groups: (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.

(in real terms) from non-financial corporate issuances in the U.S. exhibit substantial growth over the period 1985-2014. Proceeds represent about $1.2 trillion in 1985-1989 and $2.8 trillion in 2010-2014.\textsuperscript{10} The second salient pattern of Figure 2 is that the growth in proceeds was due to new financial products, as old products generated about the same amount over the entire period 1985-2014. The share of proceeds originating from new financial products increased over time, representing more than half of proceeds in the most-recent years. Most of these new products generate a relatively small share of proceeds in the entry period (dark-red bar) but eventually contribute a large share as they mature in the market (light-red bar).

The evolution of total proceeds is driven by the issuance of a varied set of financial products. Figure 3 shows the evolution of the number of distinct financial products issued by firms in each quinquennial 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 figure plots the number of products decomposed into new (entrants and young) and old products. The dark-red bar shows the number of entrant products. New products account for the majority of products issued by firms (between 55-80% depending on the period). Over the entire 1985-2014 period more than 600 distinct new financial products were introduced, and a large number of new products were first used in the first half of

\textsuperscript{10}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.
the sample, with innovation activity peaking in the quinquennial 1995-99. Approximately 40% of the new products were first introduced through a private issuance, with a significant number subsequently being publicly issued as well.

Importantly, the decomposition in Figure 3 indicates substantial churn from the entry and exit of products. By comparing the entrants (light-red) and young products (created after 1985 but not entrants), we see that firms stopped using some of new products from previous periods. For example, in the period 1990-94 firms used 260 new products, out of which 170 products were introduced in that period, and only 90 were first issued in the period 1985-99. Some of these new products were used only for a few periods. The products **Extendible Mortgage Bonds** and **Variable Rate Remarketed Bonds** are examples of products that were only issued in the period 1985-90. New products exit the market at the average rate of 40% per period.\(^{11}\) Old (blue bar) financial products also exit the market, at the slower rate of 16% per period. Naturally, some products, such as **Common Shares** and **Global Notes**, are issued in each quinquennial, while some other old products like **Mortgage Notes** and **Sinking Fund Debentures** were not issued in recent years.

### 2.2.2 Accounting for Differences in Product Novelty

By using SDC’s categorization of issuances as the baseline unit of analysis, we do not \textit{ex-ante} distinguish between major and minor changes to financial products. Since we are also interested in evaluating the \textit{degree} of novelty of each new financial product relative to existing products, we propose a methodology for quantifying the similarity of pairs of products. The converse of similarity is difference, of course, which provides a ready measure of novelty.

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.\(^{12}\) 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

\(^{11}\) We compute the exit rate as the share of new products (entrants and young) in \(t - 1\) that are new-young products in \(t\).

\(^{12}\) 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.
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 \( \text{Lease-Backed Certificates} \), while the product \( \text{Senior Pay-In-Kind Notes} \) is similar to \( \text{Senior Subordinated Pay-In-Kind Notes} \), and \( \text{Lease Bonds} \) and \( \text{Senior Pay-In-Kind Notes} \) are quite distinct. In Appendix B.4 we provide a technical description of the procedure and statistics of the dissimilarity scores.

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 the most-similar product that was created before product \( i \):

\[
N_i = 1 - \max\{s_{i1} \times 1_{\{c1 < ci\*\}}, \ldots, s_{ij} \times 1_{\{cj < ci\*\}}, \ldots, s_{iN} \times 1_{\{cN < ci\*\}}\}
\]

where cohort \( ci \) is the year in which product \( i \) first appeared, and \( 1_{\{cj < ci\*\}} \) is a dummy to indicate that product \( j \) was created before product \( i \). The novelty measure 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. Our results indicate that, for example, the products \( \text{Trust Originated Preferred Securities} \) and \( \text{Quarterly Income Capital Securities} \) are very novel, while the products \( \text{Convertible Exchangeable Preferred Shares – Series A} \) and \( \text{Floating Rate Asset Backed Certificates} \) represent relatively minor innovations on existing products.

Figure 4 charts the distribution of novelty by entry period. The average novelty is less than 0.3, indicating that many of the distinct new products represent only minor changes relative to existing products. Moreover, the patterns are very similar for different cohorts of products. Indeed, although novelty varies greatly, the distribution of product novelty is very stable over time. This stable distribution means that the patterns over time are similar, whether we use the numbers of new products documented or new products weighted by novelty.\(^{13}\)

Throughout the paper we use both the number of new financial products and the measures of novelty to represent innovation in financial products. These measures together encapsulate the act of experimentation that leads to differentiated financial products, offering variety in response to market pressures from both sudden and gradual changes in the needs of either financial institutions and investors.

\(^{13}\)Figure 9 in Appendix B.4 shows the evolution the number of new financial products weighted by novelty, and the overall pattern is very similar to the patterns in Figure 3.
investors or the firms raising funds.

2.3 Distribution of Financial Products

The size of financial products can be measured across different margins, such as total funds raised (proceeds), how frequently they are issued (issuances), and how many firms or sectors use it (issuer firms or sectors). Throughout our analysis we consider different margins and we emphasize the differences between “new” and “old” products.

The size distribution of financial products exhibits a strikingly skewed pattern, whether measured in terms of proceeds, number of issuances, or number of issuers. Table 1 presents summary statistics of issuances of corporate securities over the period 1985-2014. 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.\textsuperscript{14} 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

\textsuperscript{14}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 12 in the Appendix D show that the HHI ranges between 0.58 and 1.
Table 1: Descriptive Statistics

<table>
<thead>
<tr>
<th></th>
<th>Obs</th>
<th>Mean</th>
<th>St.Dev.</th>
<th>P25</th>
<th>P50</th>
<th>P75</th>
<th>P90</th>
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<tbody>
<tr>
<td><strong>Sector × product × period</strong></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Proceeds</td>
<td>20,400</td>
<td>566</td>
<td>1,784</td>
<td>47</td>
<td>152</td>
<td>430</td>
<td>1,164</td>
</tr>
<tr>
<td>Issuances</td>
<td>20,400</td>
<td>4</td>
<td>11</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td>Issuer firms</td>
<td>20,400</td>
<td>2</td>
<td>6</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>4</td>
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<tr>
<td><strong>Sector × period</strong></td>
<td></td>
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</tr>
<tr>
<td>Proceeds</td>
<td>3,674</td>
<td>3,142</td>
<td>11,232</td>
<td>135</td>
<td>499</td>
<td>1,840</td>
<td>6,259</td>
</tr>
<tr>
<td>Issuances</td>
<td>3,674</td>
<td>20</td>
<td>56</td>
<td>2</td>
<td>5</td>
<td>15</td>
<td>41</td>
</tr>
<tr>
<td>Issuer firms</td>
<td>3,674</td>
<td>12</td>
<td>31</td>
<td>2</td>
<td>4</td>
<td>10</td>
<td>27</td>
</tr>
<tr>
<td>Active products</td>
<td>3,674</td>
<td>6</td>
<td>7</td>
<td>2</td>
<td>3</td>
<td>7</td>
<td>12</td>
</tr>
<tr>
<td><strong>Product × period</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proceeds</td>
<td>1,676</td>
<td>6,887</td>
<td>33,923</td>
<td>117</td>
<td>415</td>
<td>1,562</td>
<td>7,951</td>
</tr>
<tr>
<td>Issuances</td>
<td>1,676</td>
<td>43</td>
<td>232</td>
<td>1</td>
<td>3</td>
<td>9</td>
<td>45</td>
</tr>
<tr>
<td>Issuer firms</td>
<td>1,676</td>
<td>27</td>
<td>163</td>
<td>1</td>
<td>2</td>
<td>7</td>
<td>29</td>
</tr>
<tr>
<td>Issuer sectors</td>
<td>1,676</td>
<td>12</td>
<td>41</td>
<td>1</td>
<td>2</td>
<td>6</td>
<td>22</td>
</tr>
<tr>
<td><strong>Product</strong></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Proceeds</td>
<td>751</td>
<td>15,370</td>
<td>102,573</td>
<td>154</td>
<td>614</td>
<td>2,384</td>
<td>10,408</td>
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<tr>
<td>Issuances</td>
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<td>1</td>
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<td>57</td>
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<tr>
<td>Issuers</td>
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<td>540</td>
<td>1</td>
<td>3</td>
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<td>42</td>
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<td>Sectors</td>
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<td>16</td>
<td>55</td>
<td>1</td>
<td>3</td>
<td>8</td>
<td>31</td>
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<tr>
<td>Duration</td>
<td>626</td>
<td>2.3</td>
<td>1.7</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>5</td>
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<tr>
<td>Novelty</td>
<td>596</td>
<td>0.28</td>
<td>0.15</td>
<td>0.16</td>
<td>0.26</td>
<td>0.36</td>
<td>0.47</td>
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</table>

Notes: The table provides various descriptive statistics of the baseline datasets used in the paper: sector × product × period level, sector × period level, product × period level, and product 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), and novelty (computed as described in the paper).

product lasts for about two 5-year periods, indicating that some products may be associated with experimentation or some short-lived needs of issuers.

When comparing the distribution of “new” and “old” products in terms of total proceeds, it is clear that each new product generates on average 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). To better understand why the total proceeds are less than expected, we decompose proceeds into quantity (the number of issuances) and value (proceeds per issuance) components. Figure 5 shows that most new products are issued less frequently than old products. Indeed, the top 90 percentile of issuances of new products is only slightly above the median of old products issued. Nevertheless, the proceeds per issuance are on average similar between old and new products (although with higher dispersion). These results indicate that the contribution of new financial products to overall proceeds comes from a large amount of distinct products
that are not used widely, but that generate a similar amount of funding for the few firms that use them.

Overall, the empirical patterns have three important implications for our analysis. First, the small number of issuers per financial product suggests that the competition between issuers is imperfect. Second, issuers in the same sector share relevant characteristics in common, and we find a very high correlation between the results whether we use issuers or sectors as the unit of interest, suggesting that firms in the same sector use financial products similarly. The third implication is that the set of available products and its suitability may vary across issuers and sectors, especially among new products. These facts motivate the model discussed in the next section, which we use to explore the mechanisms underlying the increasing specialization of financial products. We will then revisit the above-reported facts through the lens of the model.

3 Conceptual Framework

In this section, we model the allocation of financial products across firms in different sectors. The objective of the framework is to enable us to employ a structural decomposition approach to account for various forces that contribute to the variation in firms’ success in raising funds.
We consider a system in which firms obtain funds by issuing financial products, which are then acquired and traded by investors. A financial product’s payoff to investors depends on its productivity and sector- and firm-specific risk factors. Similarly to Callander, Lambert and Matouschek (2022), financial products are both horizontally differentiated (across sectors) and vertically differentiated (within sector). The model implements the oligopoly market structure in which firms consider that any offering of a financial product to investors will affect prices; investors take prices as given. Although the model is static, we consider that innovation in financial products can have an impact on the set of products that firms in a sector can use. All proofs relevant to this section are collected in Appendix A.

### 3.1 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 $I_s$ of financial products that firms can choose to issue in order to raise funds from investors. 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.

A firm $\ell \in L_s$ in sector $s$ chooses one type of financial product $i \in I_s$ that she can issue at the beginning of the period. A financial product $i$ represents a vector of characteristics $c_i$ that maps an issuer $\ell$ risk-factors, captured by a random variable $\theta_{\ell}$, 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 $\ell$ issues financial product $i$, then the resulting claim $W_{i\ell}$ is

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

The functions $x_{is}(c_i)$ and $z_{is}(c_i)$ describe how the characteristics of product $i$ affect the payoff that investors receive for each realization of $\theta_{\ell}$. 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

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15 These conditions of imperfect competition between firms are consistent with the patterns in Section 2.3.
16 We take as given that multiple financial products are potentially available in a sector, relying on an extensive literature that microfound departures from the Modigliani and Miller result. See Allen and Barbalau (2022) for a recent survey.
Specification (1) implies that 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 $\ell$. Under one interpretation, for instance, 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, $c_i$, 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.

For each financial product $i$ issued by firms in sector $s$ let

$$\chi_{is} = \frac{x_{is}(c_i)}{z_{is}(c_i)}. \quad (2)$$

We refer to $\chi_{is}$ as the productivity of the match between financial product $i$ and issuers in sector $s$. A product with a higher sector-specific productivity $\chi_{is}$ implies that the claim $W_{i\ell}$ provides investors a higher expected value per unit of risk for any issuer $\ell$ 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.

The riskiness, $\theta_\ell$, of issuer $\ell$ in sector $s$ is composed of a common component for all firms in the sector, $\theta_s$, and an idiosyncratic component specific to the firm, $\varepsilon_\ell$, 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 $\nu(\theta_s) = \sigma^2_s$ differ across sectors, while $\nu(\varepsilon_\ell) = \sigma_{\varepsilon_s}$ is the same for all firms $\ell \in L_s$. At the same time $\text{cov}(\varepsilon_\ell, \varepsilon_{\ell'}) = 0$ for any $\ell, \ell'$. For the sake of tractability, we assume that $\text{cov}(\theta_s, \theta_{s'}) = 0$, so that $\text{cov}(\theta_\ell, \theta_{\ell'}) = 0$ 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 $\ell$ and $\ell'$ in sector $s$. In particular, the correlation between any two claims $W_{i\ell}$ and $W_{i\ell'}$ issued by firms
\( \ell \) and \( \ell' \) in the same sector \( s \) is given by

\[
\rho_s \equiv \text{Corr}(W_{i\ell}, W_{i\ell'}) = \frac{\sigma^2_s}{\sigma^2_s + \sigma^2_{\varepsilon_s}}.
\]

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 \( W_{i\ell} \). We implicitly assume that firm \( \ell \) invests the proceeds \( p_{i\ell}a_{i\ell} \) in a project which returns in expectation one dollar per dollar invested,\(^{17}\) and that the firm has deep pockets and can use other assets to pay the payoff \( W_{i\ell} \) to investors with certainty, so no default occurs.

### 3.2 Investor demand

The demand for securities arises from a continuum of investors. We assume that investors are segmented over financial products. Investors segmentation is prevalent in financial markets. 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 \( i \in \mathcal{I}_s \). To allow for the possibility that some sectors are more attractive to investors than others, we consider that an investor \( n \) can participate only in a subset of sectors \( S_n \subseteq S \). However, investor \( n \) can trade all claims issued by firms \( \ell \in L_{is} \) in any sector \( s \in S_n \). Let \( \eta_{is} \) be the mass of investors that acquire financial product \( i \) in sector \( s \). For the sake of tractability, we assume that \( \eta_{is} = \eta_{i's} = \eta_s \) for any financial product \( i, i' \in \mathcal{I}_s \).

\(^{17}\)The model implications are robust to assuming that the project has an expected return larger than one.
In typical financial markets, investor demand for financial products is shaped by a mean-variance trade-off. For this reason, we assume that investors have mean-variance preferences. Each investor \( n \) who purchases financial product \( i \) is also subject to a random preference shock \( \zeta_n \) that shifts her marginal utility of consumption, as follows

\[
U^n = \zeta^n E(C^n) - \frac{\gamma}{2} V(C^n) - \sum_{s \in S_n} \sum_{\ell \in L_{is}} p_{i\ell} q_{i\ell}^n
\]  

(4)

where \( q_{i\ell}^n \) is the quantity of the claim that the investor is holding \( W_{i\ell} \) and \( C^n \) is the total consumption determined as \( C^n = \sum_{s \in S_n} \sum_{\ell \in L_{is}} q_{i\ell} W_{i\ell} \).\(^{18}\) The shock \( \zeta_n \) is independently distributed across investors, according to the distribution \( F(\cdot) \) with mean \( \mu_\zeta \) and standard deviation \( \sigma_\zeta \). The realization of the shock \( \zeta_n \) is also independent of the realization of both the sector-specific and firm-specific shocks, \( \theta_s \) and \( \epsilon_\ell \). In essence, the shock \( \zeta_n \) affects how an investor \( n \) values a claim \( W_{i\ell} \); the shock can be interpreted as introducing differences in liquidity needs, in the use of securities as collateral, in technologies to repackage and resell cash flows, or in risk-management constraints.

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). Each investor \( n \) learns \( \zeta_n \) before trading occurs. Thus, \( \zeta_n \) introduces a layer of heterogeneity across investors at the moment of trading. 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 \( W_{i\ell} \).

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

\[
p_{i\ell}(a_{i\ell}) = \mu_\zeta E(W_{i\ell}) - \frac{\gamma}{2} \zeta^2 \left( \sigma^2_s + \sigma^2_\epsilon \right) \left( (1 - \rho_s) a_{i\ell} + \rho_s \sum_{\ell' \in L_{is}} a_{i\ell'} \right)
\]  

(5)

Lemma 1 shows that the inverse demand for claim \( W_{i\ell} \) is decreasing in the quantity, \( a_{i\ell} \), that firm \( \ell \) supplies to investors, but also in the aggregate supply, \( \sum_{\ell' \in L_{is}} a_{i\ell'} \), that firms issuing product \( i \) provide to investors. As long as the payoffs of two claims \( W_{i\ell} \) and \( W_{i\ell'} \) are correlated, investors can at least partially substitute between them when deciding on the holdings in their portfolios. Thus, an investor adjusts her holding of a claim \( W_{i\ell} \) in response to both the price \( p_{i\ell} \) and the prices of all other claims, \( \{W_{i\ell'}\}_{\ell' \neq \ell} \) on the market. For instance, if the price of claim \( W_{i\ell'} \) decreases, an investor may find it beneficial to buy more of \( W_{i\ell'} \).

\(^{18}\) \( E \) and \( V \) are the expected-value and variance operators.
and less of $W_{i\ell}$, ceteris paribus. Thus, when issuer $\ell'$ 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. Moreover, the stronger the correlation $\rho_s$ is, the more investors substitute between two claims $W_{i\ell}$ and $W_{i\ell'}$, and the more the inverse demand is affected by aggregate supply. Conversely, when the correlation $\rho_s$ is weak and claims provide more diversification benefits, investors substitute less. In the limit $\rho_s \to 0$, the inverse demand for claim $W_{i\ell}$ is independent of the aggregate supply of financial product $i$ in sector $s$, $\sum_{\ell' \in L_i} a_{i\ell'}$.

### 3.3 Equilibrium

Firm $\ell$ in sector $s$ chooses the financial product $i$ and quantity $a_{i\ell}$ to issue in order to maximize her expected payoff given by (3). Issuer $\ell$ faces inverse demand (5) and understands that she has market power. Thus, when choosing the quantity $a_{i\ell}$ to issue, a firm $\ell$ must take into account the quantity, $a_{i\ell'}$, issued by the other firms $\ell' \in L_i$. Similarly, when firm $\ell$ 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 $\{L_{i\ell}\}_{i \in I_s}$ and a set $I_s \subseteq I_s$ of issued financial products, as well as quantities $\{a_{i\ell}^*\}_{i \in I_s, \ell \in L_{i\ell}}$ such that

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

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

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

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

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

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 $\ell$ that chooses to issue quantity $a_{i\ell}$ of product $i$ is

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

(6)
where \( p_{i\ell} \) represents the inverse demand in Equation (5). The first term in (6) represents the marginal benefit that firm \( \ell \) obtains by supplying an additional unit of claim \( W_{i\ell} \) to investors. However, increasing the quantity supplied carries an indirect cost in the impact this quantity has on the price in the market for claim \( W_{i\ell} \). The second term in the first-order condition (6) reflects this indirect cost. To track the role that market power has on firms’ decisions we use a standard measure, namely the ratio of price minus marginal cost to price, or the Lerner index defined in our setup as

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

The Lerner index ranges between 0 and 1, and a lower value signifies that firm \( \ell \) has less market power. The following proposition characterizes the equilibrium quantity that each firm \( \ell \) issuing product \( i \) supplies,

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

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

and

\[
\Lambda_{i\ell} \equiv \Lambda_{is} = \frac{(\mu_{\zeta} - 1)}{(L_{is} - 1) \rho_s + \mu_{\zeta} + 1}
\] (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 \( \eta_s \) or a lower risk aversion \( \gamma \). Conversely, in sectors with more risk, measured by either sectoral volatility, \( \sigma_s^2 \), or idiosyncratic firm volatility, \( \sigma_{\varepsilon_s}^2 \), the firm issues less, all else equal. Moreover, as more firms choose to issue product \( i \) and firm \( \ell \) has less market power she 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 \( \ell \), as the first-order condition
(6) implies that the expected payoff to firm $\ell$ is given by

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

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

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

(10)

where $\chi_{is}$ was defined in Equation (2) as the productivity of the financial product $i$. Thus, firms prefer higher-productivity products. At the same time, firms prefer products for which there this limited competition and they can exercise more market power. The tension between the productivity of a product and a firm’s market power when issuing that product shapes the equilibrium distribution of issuers across products. The following proposition formalizes this reasoning.

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

$$\chi_{is} \frac{\Lambda_{is}}{1 - \Lambda_{is}} = \chi_{i's} \frac{\Lambda_{i's}}{1 - \Lambda_{i's}},$$

(11)

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

If condition (11) holds, then an issuer $\ell$ of product $i$ with $L_{is}$ issuers would not want to deviate and issue product $i'$ with $L_{i's}$ issuers. Firm $\ell$ 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 $\ell$ 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 $\ell'$ 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 that are issued in equilibrium depends on the set of products available to a sector, and not all products available to a sector $s$ must be issued in equilibrium. To see this, consider the special case in which only two products are available to sector $s$, so that $I_s = \{i, i'\}$, 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 difference in the two products’ productivity is sufficiently small, 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 \( I_s = \{ i \mid s.t. \ L_{is} \geq 1 \} \) of financial products issued in equilibrium by firms in sector \( s \).

1. The lowest-productivity product, \( \chi_{is}^{\text{min}} \), that is issued in equilibrium in sector \( s \) satisfies the following condition
   \[
   \chi_{is}^{\text{min}} \geq \frac{1}{1 + \frac{\rho_s}{2} \left( \frac{L_s}{I_s} - 1 \right)} \sum_{i \in I_s} \chi_{is}.
   \] (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 \( \ell \) 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.
3.4 Financial Innovation and Proceeds

Financial innovation expands the variety of financial products that firms in a sector can access. In our framework, financial products are technologies that each firm can use to issue a state-contingent financial claim. This way, we depart from the traditional role of financial innovation in creating value by completing markets through spanning, and instead emphasize the role that larger variety of products can have in creating value.

To illustrate this point, it is useful to derive the total proceeds obtained by issuers in a given sector, taking into account that multiple products are potentially issued in equilibrium. We first obtain the expected proceeds of firm $\ell$ in sector $s$ that issues product $i$ in equilibrium, $E(p_{i\ell}) \times a_{i\ell}$, by substituting the optimal quantity, $a_{i\ell}$, issued by each firm $\ell$, as described by (8), into the price (5) which yields

$$E(p_{i\ell}) \times a_{i\ell} = \lambda_{is}^2 \frac{1}{\sigma_s^2 + \sigma_{\epsilon_s}^2} \frac{\Lambda_{is}}{(1 - \Lambda_{is})^2} \eta_s \gamma,$$

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 as follows

$$Y_s \equiv \sum_{i \in I_s} \sum_{\ell \in L_{is}} E(p_{i\ell}) \times a_{i\ell}$$

$$= \left( \sum_{i \in I_s} \chi_{is} \right)^2 \frac{1}{\sigma_s^2 + \sigma_{\epsilon_s}^2} \frac{\sum_{i \in I_s} \omega_{is} \lambda_{is}}{\sum_{i \in I_s} (1 - \Lambda_{is})^2} \eta_s \gamma,$$

(13)

where $\omega_{is}$ represents the share of total proceeds in sector $s$ that the issuance of product $i$ accounts for. The derivations are provided in Appendix A.

When innovation allows firms within a sector $s$ to access a richer the set of products relative to a sector $s'$, firms in sector $s$ can benefit both from access to more types of products, as well as from access to more pools of investors. Having more types of products to chose from has an impact on proceeds on its own. Indeed, the set of products issued in equilibrium in sector $s$ can have, on average, higher productivity than in sector $s'$. Thus, even if the number of products issued in equilibrium in the two sectors, as well as the distribution of issuers across products is the same, the quantity that firms issue will be different. This explains why the sector in which firms issue products that are of higher average productivity reaps the greater proceeds, as Equation (13) implies.
More generally, the entire distribution of the productivity of financial products within a sector affects proceeds. For instance, even when the average productivity of financial products issued in equilibrium is the same across two sectors, the sector with a higher dispersion in productivity obtains higher proceeds, ceteris paribus. The intuition relies on the observation that the higher the productivity the more attractive a product is to firms. Thus, in equilibrium, the distribution of issuers across products is more skewed towards higher-productivity products in the sector with a higher dispersion in product productivity. With more issuers issuing more high-productivity products, the proceeds in sector $s$ are larger.

Besides financial innovation, both demand and supply factors shift proceeds. Proceeds are clearly larger when a sector faces stronger demand, proxied either through a higher $\eta_s$ or $\mu_\zeta$, or lower $\gamma$. On the supply side, differences in riskiness across sectors and firms affect proceeds. Ceteris paribus, sectors with greater uncertainty generate lower proceeds. Likewise, a sector facing more uncertainty will have return lower proceeds (at least as long as $\mu_\zeta \leq 3$). The ceteris paribus assumption includes keeping the set of products issued in equilibrium remains the same. Note 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 Model-based Decomposition

In this section, we use the conceptual framework we developed in Section 3 to quantify the contribution that the different sources of sector heterogeneity make to the dispersion in firms’ ability to raise external funding. Using the model, we estimate that the productivity of financial products used by various sectors makes a sizeable contribution to explaining the dispersion of the growth rates of proceeds generated by the issuance of new securities.

4.1 The Sources of Heterogeneity

The ability of different issuers to raise external funds is measured best by the total proceeds collected by its sector. Total proceeds will reflect multiple sources of heterogeneity among sectors. In particular, taking logs in Equation (13), we obtain that the log proceeds of sector
s in period $t$ can be expressed as:

$$
\log Y_{st} = 2 \log \left( \frac{\sum_{i \in I_{st}} \chi_{ist}}{I_{st}} \right) \quad \text{Average productivity}
$$

$$
+ \log \left( \sum_{i \in I_{st}} \frac{\omega_{ist} \Lambda_{ist}}{I_{ist}} \right) \quad \text{Market power & Risk}
$$

$$
+ \log \left( \frac{1}{\sigma_{ist}^2 + \sigma_{\varepsilon ist}^2} \right) \quad \text{Demand}
$$

Equation (14) shows that log proceeds can be decomposed broadly into three additive and separable components. The first component captures the average productivity of products used by the sector, the second component combines market power and risk of issuers, and the final component captures the investors demand.

The decomposition in Equation (14) depends on both observable and unobservable variables $\{L_{ist}, \omega_{ist}, \chi_{ist}, I_{st}, \eta_{ist}\}$, for any set of parameters $\{\mu, \gamma, \sigma_{ist}, \sigma_{\varepsilon ist}\}$. Indeed, while we observe the number of distinct issuers $L_{ist}$, the proceeds weights $\omega_{ist}$, and the set of distinct products $I_{st}$, we cannot directly observe the productivity of the financial products $\chi_{ist}$ and the mass of investors $\eta_{ist}$. 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 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

$$
\log \eta_{ist} = \log \eta_s + \log \psi_t
$$

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 4.2.
Proposition 3 If Assumption 1 holds, changes in (log) proceeds will be:

\[
\Delta^{s,t} \log(Y_{st}) = \Delta^{s,t} 2 \log \left( \frac{\sum \chi_{ist}}{I_{st}} \right) + \Delta^{s,t} \left[ \log \left( \frac{\sum \omega_{ist} \Lambda_{ist}}{I_{ist}} \right)^{2} + \log \frac{1}{(\sigma_{st}^2 + \sigma_{\varepsilon st}^2)} \right]
\]

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 market power and risk, respectively.

The proof is provided in Appendix C.

An important 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 \(\Delta^{s,t} \log(Y_{st})\) and the double difference of the market power and risk component, \(\Delta^{s,t} Z_{st}\). To see this, note 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, \(\omega_{ist}\), associated with product \(i\). Given a set of parameters, we can then impute the Lerner index, \(\Lambda_{is}\), based on Equation (9), and obtain \(\Delta^{s,t} Z_{st}\).

4.2 Estimation of Parameters

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

To obtain measures of sector risk, \(\sigma_{st}^2\), and firm-specific risk, \(\sigma_{\varepsilon st}^2\), 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 equation

\[
\Delta w_{\ell sa} = \delta_{sa} + \beta_{1s} \ln(size_{\ell sa}) + \beta_{2s} \ln(age_{\ell sa}) + \varepsilon_{\ell sa} \tag{15}
\]

where the outcome variable, \(\Delta w_{\ell sa}\), is either earnings growth (baseline) or sales growth (robustness) of firm \(\ell\) in sector \(s\) in year \(a\).\(^{19}\) While sales data is more widely available, we

\(^{19}\)Our measure of annual sales growth is scaled to the average sales in the current and previous years and our measure of earnings growth is scaled to the average assets in the current and previous years.
Table 2: Statistics on Estimated Parameters

<table>
<thead>
<tr>
<th>Sector and idiosyncratic risk</th>
<th>Mean</th>
<th>Std.Dev.</th>
<th>P25</th>
<th>P50</th>
<th>P75</th>
</tr>
</thead>
<tbody>
<tr>
<td>Earnings growth ( \sigma_{st} )</td>
<td>0.04</td>
<td>0.03</td>
<td>0.02</td>
<td>0.03</td>
<td>0.05</td>
</tr>
<tr>
<td>( \sigma_{\varepsilon_{st}} )</td>
<td>0.21</td>
<td>0.11</td>
<td>0.13</td>
<td>0.18</td>
<td>0.28</td>
</tr>
<tr>
<td>Sales growth ( \sigma_{st} )</td>
<td>0.07</td>
<td>0.06</td>
<td>0.04</td>
<td>0.06</td>
<td>0.09</td>
</tr>
<tr>
<td>( \sigma_{\varepsilon_{st}} )</td>
<td>0.29</td>
<td>0.12</td>
<td>0.21</td>
<td>0.28</td>
<td>0.35</td>
</tr>
<tr>
<td>Demand proxies</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \Delta \log(\text{market value}) )</td>
<td>0.16</td>
<td>0.64</td>
<td>-0.10</td>
<td>0.20</td>
<td>0.48</td>
</tr>
<tr>
<td>Price-earnings ratio</td>
<td>7.2</td>
<td>2.6</td>
<td>5.2</td>
<td>6.7</td>
<td>8.3</td>
</tr>
</tbody>
</table>

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 B.2 for details.

think earnings are more relevant to payoffs in the model. We control for size and age as those may be known sources of uncertainty. For sector-specific risk in each sector and 5-year period, we compute the standard deviation of the estimated annual sector-time fixed effects, \( \delta_{sa} \). 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 2 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 for earnings-based sector risk of 0.03 and the same statistic for idiosyncratic risk of 0.18. 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 more absolute dispersion than sector risk when we focus on risk proxies based on sales.

We evaluate the adequacy of Assumption 1 about the evolution of the mass of investors across sectors by using two external proxies: an index for market value and a price-earning ratio. The variables vary with the sector and period. The last two rows of table 2 report statistics on these sector-specific demand proxies, also computed from Compustat firm-level data. This verification exercise confirms that the assumption is aligned with patterns in the data.

4.3 Results

We begin by assessing whether our estimates and decomposition are reasonable by computing simple correlations. In Table 3 we present the cross-sectional correlation between the double
Table 3: Statistics on Components

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>$\Delta^{s,t}Y_{st}$</th>
<th>$\Delta^{s,t}\bar{\chi}_{st}$</th>
<th>$\Delta^{s,t}Z_{st}$</th>
<th>$\Delta^{s,t}L_{st}$</th>
<th>$\Delta^{s,t}I_{st}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta^{s,t}Y_{st} = \Delta^{s,t}\bar{\chi}<em>{st} + \Delta^{s,t}Z</em>{st}$</td>
<td>0.00</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average productivity</td>
<td>0.00</td>
<td>0.74</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market power and risk</td>
<td>0.00</td>
<td>0.49</td>
<td>-0.23</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number Issuers</td>
<td>0.00</td>
<td>0.19</td>
<td>-0.00</td>
<td>0.28</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Number Products</td>
<td>0.00</td>
<td>0.34</td>
<td>0.06</td>
<td>0.42</td>
<td>0.71</td>
<td>1</td>
</tr>
</tbody>
</table>

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, number of financial products, and the coefficient of variation. The first column shows the average, and the remaining columns display pairwise correlation coefficients. We use the sector × period dataset, and for all variables we apply the double-difference operator for sector and period. Sectors are defined with 4-digit SIC codes.

The difference of log proceeds, $\Delta^{s,t}\log(Y_{st})$, and its components. Note that because we use double differences $\Delta^{s,t}$, the average of each component is zero. These correlations yield several insights. First, sectors with higher growth in proceeds have higher-productivity financial products on average, as well as higher market power and risk components. Second, the correlation between the average productivity component and the market power and risk component is negative, which indicates that productivity increased relatively more in sectors in which market power and risk declined relatively more. This negative correlation is not significantly explained by the determinants of the market power and risk component, such as the number of issuers, or the number of product types. Third, sectors with higher growth in proceeds and in the market power and risk component also exhibited higher growth in the numbers of issuers and of financial products.

Next, 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). These decompositions use 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 market power and risk ($\Delta^{s,t}Z_{st}$). We implement the decomposition by estimating

$$
\Delta^{s,t}\bar{\chi}_{st} = \beta_{\text{average productivity}} \Delta^{s,t}Y_{st} + e_{st}
$$

$$
\Delta^{s,t}Z_{st} = \beta_{\text{market power & risk}} \Delta^{s,t}Y_{st} + v_{st}
$$

Appendix C discusses two crucial properties of this variance decomposition. First, the terms
Table 4: Variance Decomposition

<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th>$\Delta^{s,t} \Delta \log Y$</th>
<th>Alternatives</th>
<th>Demand</th>
<th>Demand</th>
<th>Issuers</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average productivity</td>
<td>0.66</td>
<td>0.63</td>
<td>0.61</td>
<td>0.66</td>
<td>0.57</td>
<td>0.66</td>
<td></td>
</tr>
<tr>
<td>Market power and risk</td>
<td>0.34</td>
<td>0.37</td>
<td>0.34</td>
<td>0.34</td>
<td>0.43</td>
<td>0.34</td>
<td></td>
</tr>
<tr>
<td>Demand</td>
<td></td>
<td>-</td>
<td>0.05</td>
<td>0.00</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
</tbody>
</table>

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 changes 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.

in the decomposition need not be independent. Also, note that 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 $\beta_{average\ productivity} + \beta_{market\ power\ &\ risk} = 1$).

Table 4 shows the baseline estimated components $\beta_{average\ productivity}$ and $\beta_{market\ power\ &\ risk}$ 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 66% 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 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 of proceeds (instead of double-differences in levels), and we find few differences in the impact. Second, we applied the decomposition with the external proxies for the sector-period mass of investors – a market-value index and a price-earning ratio – and we find little impact on the importance of average productivity. This evidence supports the hypothesis that assumption 1 matches the data well. Third, we compute an alternative component for capturing market power and
risk that uses the number of issuances instead of the number of issuers. The differences in these variables that capture the supply of securities will come from the fact that some firms issue a product multiple times over a period, though we are effectively treating each issuance as independent with our use of issuances as the variable of interest. 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.\footnote{In Appendix D, we also show the results for different values of $\mu_\zeta$; these are quantitatively almost equal. They are equal because the double difference of the component of risk and dispersion is unchanged.}

5 The Role and Nature of Innovation

The previous section showed that changes in the average productivity of financial products play a crucial role in explaining differences across sectors in raising funds. We now go a step further and examine the drivers of changes in the productivity of financial products used by distinct sectors. First, we show that the innovations represented by new financial products are responsible for increases in average productivity. Second, we show that there is substantial heterogeneity in the adoption of financial products across firms, particularly of new products. Because new products are relatively more sector-specific, they contribute to the differences in average productivity between sectors. This last result indicates that a substantial component of innovation in the financial sector is akin to the product variety and horizontal differentiation documented in non-financial markets.

5.1 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 $t-1$ and $t$, we distinguish between financial products available in both periods $\mathcal{I}_t^c$, new-entrant products $\mathcal{I}_t^n$ (that is, the set of products in $t$ but not in
Changes in average productivity can then be written as a function of two sets of terms:

\[
\Delta \bar{\chi}_{st,t} = \sum_{i \in I_t^c} \left( \chi_{ist} \frac{d_{ist}}{\sum_{i \in I_t} d_{ist}} - \chi_{ist(t-1)} \frac{d_{ist(t-1)}}{\sum_{i \in I_{t-1}} d_{ist(t-1)}} \right) + \sum_{i \in I_n^t} \left( \chi_{ist} \frac{d_{ist}}{\sum_{i \in I_t} d_{ist}} - \chi_{ist(t-1)} \frac{d_{ist(t-1)}}{\sum_{i \in I_{t-1}} d_{ist(t-1)}} \right)
\]

Continuing

Entry & Exit (16)

The first set captures changes in the contribution of continuing products, which are present in both periods \( t - 1 \) and \( t \). It includes a “within” subcomponent that captures changes in productivity of products and a “between” subcomponent that results from changes in the allocation of products in the sector. 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 existing products.

The disaggregation in Equation (16) shows that new products affect overall average productivity. When financial innovation expands the set of products available for firms within a sector, the set of products that firms issue also changes. In particular, firms find new-entrant products appealing if they offer higher productivity compared to their current product. Thus, while we cannot measure the contributions of each of the components in Equation (16) because we cannot observe \( \chi_{ist} \), we can make inferences if we observe that a new product was adopted by a sector. Insights from the model in Section 3 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.

We next turn to the data and evaluate whether the changes in average productivity estimated in the previous section are associated with variables that capture the adoption of new financial products. Our baseline measure is the degree of the adoption of new products using the share of new entrant products \( \frac{\sum_{i \in I_n^t} d_{ist}}{\sum_{i \in I_t} d_{ist}} \). Table 5 provides evidence of a positive significant association between innovation, captured through the adoption of new financial products, and the average productivity of the financial products used. An increase in the share of new products by 10 percentage points is associated with a 3.9% increase in average productivity. This positive association between the adoption of new financial products and growth in access to funds is robust to multiple alternative measures of the adoption of new products, including the the share of new entrants weighted by novelty, and the share of new...
Table 5: New financial products and average productivity

<table>
<thead>
<tr>
<th>Dep. Var.</th>
<th>( \Delta^{s,t}\bar{\chi} )</th>
<th>( \Delta^{s,t}\bar{\Delta}\bar{\chi} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ind. Var.</td>
<td>New-entrant (share)</td>
<td>Novelty (average)</td>
</tr>
<tr>
<td>Estimated Coefficient</td>
<td>0.390** (0.156)</td>
<td>0.038 (0.181)</td>
</tr>
<tr>
<td>Observations</td>
<td>2,872</td>
<td>2,945</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.126</td>
<td>0.027</td>
</tr>
<tr>
<td>Sector</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Time</td>
<td>Y</td>
<td>Y</td>
</tr>
</tbody>
</table>

Notes: The table shows the regression output from regressing equation \( D_{s,t} = \beta X_{s,t} + \alpha_s + \gamma_t + \varepsilon_{s,t} \), where the dependent variable is the double difference in productivity \( \Delta^{s,t}\bar{\chi} \), and double difference in first difference of changes in productivity \( \Delta^{s,t}\bar{\Delta}\bar{\chi} \). The data in each column results from running the regression on distinct independent variables defined at the sector-period level: Columns (1) and (4) use the share of new-entrants products (introduced in the contemporaneous 5-year period); columns (2) and (5) use the share of new-entrant products weighted by their novelty; columns (3) and (6) use the share of new-to-sector products (introduced in that sector in the contemporaneous 5-year period). The regressions use the baseline sector \( \times \) period dataset with sectors defined by 4-digit SIC codes.

entrants in sector \( s \),\(^{21}\) and others (Table 5).

5.2 The increasing specialization of financial products

While there is a clear association between firms issuing new financial products and their success in attracting external funds, most new financial products are used infrequently and by a limited number of issuers. In this section we start by showing evidence that we can only rationalize the allocation of products to sectors when the productivity \( \chi_{ist} \) of products is heterogeneous across sectors, followed by evidence that the positive association between firms issuing new financial products and their success in attracting external funds results from specialized new financial products.

5.2.1 Financial products are horizontally differentiated

There are substantial differences in the distribution of financial products across sectors when comparing new and old products. Figure 6 shows the distribution of products ranked by the number of distinct sectors issuing that product, with new and old products separated. The

\(^{21}\)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.
Figure 6: Distribution of Financial Products Among Sectors

Notes: The left figure divides new financial products by the numbers of 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 \( \times \) 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.

Two distributions differ strikingly. Most notably, about half of new products are only used by one sector in any period (e.g. Mezzanine Aircraft Notes and Power Notes), compared to only 15% for old products. This pattern suggests that most new products are specialized, while older products are more generic and broadly applicable. Indeed, 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).

The mechanism in the model in Section 3 that accounts for the heterogeneity in adoption patterns we observe in the data hinges on the productivity of a financial product being sector specific. In other words, the very same type of 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. We establish that this characterization of the data is accurate.\(^{22}\)

A testable implication that follows from the model, in particular from Corollary 1 (part 2), is that if a set of products is available in two sectors, \( s \) and \( s' \), and the productivity of

\(^{22}\)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 unique financing requirements of specific firms.
each product is the same across sectors \((\chi_{ist} = \chi_{ist}' \forall i)\), then the ranking of the products issued in equilibrium, as determined by their proceeds, will be the same in both sectors. We test this implication by computing the correlation of product rankings across sectors. In the extreme case in which the same set of products are issued in the two sectors, their rank correlation should be equal to one. When two sectors do not issue the same set of products, this is only because one issues more products of lower productivity. Indeed, the productivity cutoff can differ across sectors \((\chi_{st}^{\text{min}} \neq \chi_{s't}^{\text{min}})\), as it depends on the distribution of issuers over products in each sector, which in turn depends on the market power of issuers and the size of each sector. Even in this case, we expect the rank correlation of the two sectors to be high. For each sector and time period, we compute the rank of financial products. In Figure 7 we present the average pairwise rank correlations of those rankings for each time period. The blue line represents the average rank correlations across sector pairs for each period, while the red line represents the average rank correlations across sector pairs considering only products with positive proceeds in that period for each pair of sectors. Both rank correlations are small, consistent with our framework which allows the productivity \(\chi_{ist}\) of products to be heterogeneous across sectors.

\footnote{The unrestricted rank correlation shown in the blue line in Figure 7 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 sector \(s\) was not issued in sector \(s'\), we provide the alternative restricted exercise.}
5.2.2 The adoption of specialized new products and average productivity

While the productivity of any given product is heterogeneous across sectors, we can distinguish two groups: those with generally high average productivity and those with generally low average productivity but that exhibit a strong suitability for specific sectors. 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

$$\bar{\chi}_{st} = \sum_{i \in I_s} \left( \frac{\bar{\chi}_{it}}{\bar{\chi}_{it} \sum_{i \in I_t} d_{ist}} \right).$$

(17)

The first group are the products have high $\bar{\chi}_{it}$ and thus are likely used by many sectors. We will refer to those as “standardized” products. The second group are products that have low $\bar{\chi}_{it}$, but there are sectors for which $\chi_{ist}$ is high, such that the product is used by those sectors in equilibrium. We will refer to these as “specialized” products.\(^{24}\) Equation (17) shows that the average productivity of financial products issued by firms in a sector $s$ depends on both the adoption of standardized as well specialized products.

Although we do not directly measure the productivities $\chi_{ist}$, through the lens of our model, we can use the allocation of securities to sectors to proxy for whether they are likely “standardized” or “specialized” products. In the data, we consider products to be “specialized” if they are used by up to 5 sectors and to be “standardized” if they are used by more than 5 sectors.

We evaluate the association between changes in average productivity with the composition of standardized versus specialized products. For each sector $\times$ period, we compute the share of products that are standardized/specialized and the share of new-entrant standardized/specialized products. Using within-sector and time-period variation, we evaluate the association between these variables and average productivity. Table 6 shows that sectors that use more specialized products and more new-entrant specialized products see higher increases in average productivity. However, the use of a large amount of standardized products in a sector is associated with significantly lower growth in productivity relative to other sectors. Likewise, 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 results are robust to alternative definitions of standardized/specialized, and to using specifications in changes. Overall, we conclude that the sectors that use sector-specialized products and benefited from newly introduced sector-specialized products are

\(^{24}\) We adopt the terms “standardized” and “specialized” goods from Holmes and Stevens (2014).
Table 6: Specialized and standardized new products and average productivity

<table>
<thead>
<tr>
<th>Dep. Var.</th>
<th>All $\Delta^{s,t}\bar{\chi}$</th>
<th>New-entrant $\Delta^{s,t}\bar{\chi}$</th>
<th>All $\Delta^{s,t}\Delta\bar{\chi}$</th>
<th>New-entrant $\Delta^{s,t}\Delta\bar{\chi}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ind. Var.</td>
<td>spec. (share)</td>
<td>stand. (share)</td>
<td>spec. (share)</td>
<td>stand. (share)</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Estimated</td>
<td>0.945***</td>
<td>-0.556**</td>
<td>0.692*</td>
<td>0.041</td>
</tr>
<tr>
<td></td>
<td>(0.282)</td>
<td>(0.229)</td>
<td>(0.360)</td>
<td>(0.248)</td>
</tr>
<tr>
<td>Obs.</td>
<td>2,872</td>
<td>2,954</td>
<td>2,954</td>
<td>2,872</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.128</td>
<td>0.029</td>
<td>0.028</td>
<td>0.124</td>
</tr>
<tr>
<td>Sector</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Time</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
</tbody>
</table>

Notes: The table shows the regression output from regressing equation $D_{s,t} = \beta X_{s,t} X_{s,t} + \alpha s + \gamma t + \varepsilon_{s,t}$, where the dependent variable is the double difference in productivity $\Delta^{s,t}\bar{\chi}$, and double difference in first difference of changes in productivity $\Delta^{s,t}\Delta\bar{\chi}$. The data in each column results from running the regression on distinct independent variables defined at the sector-period level: Columns (1) and (5) use the share of products that were used by only up to 5 sectors; columns (2) and (6) use the share of products that were used by only up to 5 sectors; columns (3) and (7) use the share of new-entrant products (introduced in the contemporaneous 5-year period) that were only used by up to 5 sectors; columns (4) and (8) use the share of new-entrant products that were only used by more than 5 sectors. The regressions use the baseline data set with sectors defined at 4-digit SIC codes.

able to grow their ability to raise funds more than sectors that rely on generic products. 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.

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. To explore the role of innovation, we identify financial products created during the period of analysis – new financial products – 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 growing over time, and that new financial products are responsible for more than half of total proceeds by the end of the period of analysis.

To interpret these facts, we develop a model in which firms with market power are segmented across sectors and choose which of a set of 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 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.

The present work can be extended in several directions. First, the model could incorporate investment banks who act as intermediaries between issuing firms and investors. Second, the model is static, which allows it to capture multiple margins that affecting the ability of firms to raise funds, at the expense of a static framework. Alternatively, a simplified dynamic model with endogenous innovation might help with understanding the determinants of product-innovation decisions in the financial sector. Finally, we do not take a stand about whether a firm’s ability to raise funds affects overall performance in terms of growth and profitability. We leave these extensions for future research.
References


Han, S., Li, D., 2010. Liquidity crisis, runs, and security design - lessons from the collapse of the auction rate securities market. Finance and Economics Discussion Series.


Appendix

A 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

\[
V^n = \zeta^n \sum_{i,\ell} q^n_{i\ell} E(W_{i\ell}) - \frac{\gamma}{2} (q^n)^T \nu_W q^n - \sum_{i,\ell} p_{i\ell} q^n_{i\ell},
\]

where \( q^n \) is a column vector of the quantities of products \( W_{i\ell} \) that investor \( n \) acquires, and \( \nu_W \) is the variance covariance matrix of the products in investor \( n \)’s portfolio. Note that under our assumptions the matrix \( \nu_W \) is a block-diagonal matrix, so that on the diagonal each block represents the variance-covariance 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

\[
\zeta^n E(W_{is}) - \gamma \nu_{W_{is}} q^n_{is} - p_{is} = 0, \forall n \in \eta_{is}
\]

(A.1)

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

\[
q^n_{is} = \frac{1}{\gamma} \nu_{W_{is}}^{-1} (\zeta^n E(W_{is}) - p_{is}).
\]

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

\[
\int q^n_{i\ell} dn = a_{i\ell}, \forall \ell \in L_{is}.
\]

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

\[
\frac{1}{\gamma} \eta_{is} \nu_{W_{is}}^{-1} (\mu \zeta E(W_{is}) - p_{is}) = a_{is},
\]

42
where \( a_{i\ell} = (a_{i\ell})_{\ell \in L_{is}} \) represents a column vector of the quantities supplied by each issuer \( \ell \in L_{is} \).

Thus, it follows that
\[
p_{is} = \mu_{\zeta} E(W_{is}) - \frac{\gamma}{\eta_{is}} V_{W_{is}} a_{is},
\]
where the matrix \( V_{W_{is}} \) has \( z_{is}^2 (\sigma_s^2 + \sigma_{\varepsilon_s}^2) \) 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
\[
E(p_{i\ell} - W_{i\ell}) + \frac{\partial p_{i\ell}}{\partial a_{i\ell}} a_{i\ell} = 0
\]
or
\[
E(p_{i\ell} - W_{i\ell}) = \frac{\gamma}{\eta_{is}} z_{is}^2 (\sigma_s^2 + \sigma_{\varepsilon_s}^2) a_{i\ell}.
\]
Substituting the price \( p_{i\ell} \) given by (5), we obtain
\[
\left( (\mu_{\zeta} - 1) E(W_{i\ell}) - \frac{\gamma}{\eta_{is}} z_{is}^2 \left( \sigma_s^2 + \sigma_{\varepsilon_s}^2 \right) a_{i\ell} + \sum_{\ell' \in L_{is}} \sigma_s^2 a_{i\ell'} \right) - \frac{\gamma}{\eta_{is}} z_{is}^2 (\sigma_s^2 + \sigma_{\varepsilon_s}^2) a_{i\ell} = 0.
\]
Aggregating for all \( \ell \in L_{is} \) we can solve for
\[
\sum_{\ell \in L_{is}} a_{i\ell} = \frac{\eta_{is} (\mu_{\zeta} - 1)}{\gamma} \frac{1}{z_{is}^2 (\sigma_s^2 + 2\sigma_{\varepsilon_s}^2 + \sigma_s^2 L_{is})} \left[ \sum_{\ell \in L_{is}} E(W_{i\ell}) \right],
\]
and using that \( E(W_{i\ell}) = x_{is} \) we obtain that
\[
a_{i\ell} = \frac{x_{is}}{z_{is}^2 \left( \sigma_s^2 + 2\sigma_{\varepsilon_s}^2 + L_{is} \sigma_s^2 \right)} \frac{(\mu_{\zeta} - 1) \eta_{is}}{\gamma}.
\]
Substituting the quantities back in the price \( p_{i\ell} \) given by (5) we obtain
\[
p_{i\ell} = \frac{x_{is}}{\sigma_s^2 + 2\sigma_{\varepsilon_s}^2 + \sigma_s^2 L_{is}} \left( \sigma_s^2 + \sigma_s^2 L_{is} + \mu_{\zeta} \sigma_s^2 + \mu_{\zeta} \sigma_{\varepsilon_s}^2 \right)
\]

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

$$\Lambda_{i\ell} = (\mu_\zeta - 1) \frac{1}{(L_{is} - 1) \frac{\sigma_s^2}{(\sigma_s^2 + \sigma_{es}^2)} + 1 + \mu_\zeta}$$  \hspace{1cm} (A.3)

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

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

**Proof of Proposition 2**

Condition 2 in Definition 1 implies that a set of security types, $I_s \subset I_s$, 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

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

and, at the same time

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

Using (10), the equilibrium conditions become

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

and

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

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

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

and

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

A sufficient condition for the equilibrium is then

\[
\chi_{is} \sigma_s^2 + 2\sigma_{\xi_s}^2 + L_{is}\sigma_s^2 = 1 = \chi_{i's} \left( \sigma_{s'}^2 + 2\sigma_{\xi_{s'}}^2 + L_{i's}\sigma_s^2 \right) \tag{A.4}
\]

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 (A.4) that we derived in the proof of Proposition 2 and summing up for all \( i \in I_s \), we obtain that

\[
\frac{\chi_{is}}{\sigma_s^2 + 2\sigma_{\xi_s}^2 + L_{is}\sigma_s^2} = \frac{1}{\sigma_{s'}^2 + 2\sigma_{\xi_{s'}}^2 + L_{i's}\sigma_s^2} \sum_{i' \in I_s} \chi_{i's} \frac{\sum_{i' \in I_s} \chi_{i's}}{I_s}. \tag{A.5}
\]

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

\[
\chi_{is}^\text{min} \geq \frac{2\sigma_s^2 + 2\sigma_{\xi_s}^2 \sum_{i' \in I_s} \chi_{i's}}{(\sigma_s^2 + 2\sigma_{\xi_s}^2 + L_{is}\sigma_s^2) I_s}.
\]

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

**Part 2**

If condition (A.4) holds, this follows immediately.
Derivations of the total proceeds in sector s in Eq. 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

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

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

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

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

$$\chi_{is} \frac{\Lambda_i}{(1 - \Lambda_i)} = \frac{1}{1_s} \sum_{i' \in I_s} \chi_{is} \frac{1}{\Lambda_i} \frac{1}{\Lambda_{i'}} \sum_{i' \in I_s} \frac{L_{is}}{\Lambda_{i'}} \frac{(1 - \Lambda_{i'})}{\Lambda_i}. \tag{A.8}$$

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

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

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

$$\omega_i = \frac{\sum_{\ell \in L_{is}} E(p_{i\ell}) a_{i\ell}}{\sum_{i \in I_s} \sum_{\ell \in L_{is}} E(p_{i\ell}) a_{i\ell}}. \tag{A.10}$$

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

\[
\omega_i = \frac{L_{is}}{(1 - \Lambda_i)} \frac{1}{\Lambda_i} \frac{\eta_s}{\gamma} \left( \chi_{is} \frac{\Lambda_i}{(1 - \Lambda_i)} \right)^2 \frac{1}{\sigma_s^2 + \sigma_s^2} \sum_{i \in I_s} L_{is} \frac{1}{(1 - \Lambda_i)} \frac{1 - \Lambda_i}{\Lambda_i} \frac{\eta_s}{\gamma} \left( \chi_{is} \frac{\Lambda_i}{(1 - \Lambda_i)} \right)^2 \frac{1}{\sigma_s^2 + \sigma_s^2} \\
= \frac{L_{is}}{(1 - \Lambda_i)} \frac{1}{\Lambda_i} \frac{\eta_s}{\gamma} \left( \chi_{is} \frac{\Lambda_i}{(1 - \Lambda_i)} \right)^2 \frac{1}{\sigma_s^2 + \sigma_s^2} \sum_{i \in I_s} L_{is} \frac{1}{(1 - \Lambda_i)} \frac{1 - \Lambda_i}{\Lambda_i} \frac{\eta_s}{\gamma} \left( \chi_{is} \frac{\Lambda_i}{(1 - \Lambda_i)} \right)^2 \frac{1}{\sigma_s^2 + \sigma_s^2}
\]

which yields

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

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

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

and subtracting \( I_s \) in both sides it follows that

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

or

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

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

\[
\left( \sum_{i \in I_s} \frac{L_{is}}{\Lambda_i} \right) \left[ \sum_{i \in I_s} \left( \frac{\omega_i}{L_{is}} - \frac{1}{\sum_{i \in I_s} \frac{L_{is}}{\Lambda_i}} \right) \right] = \sum_{i \in I_s} \left( \frac{1}{\Lambda_i} - 1 \right).
\]
We can now substitute the denominator in Equation (A.9) to obtain total proceeds in sector $s$ as

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

which can also be written as

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

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

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

which is the same expression as in Equation (13).

B Data Set Construction

B.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 8 we show such comparison.

**Figure 8: Data coverage vs. Financial Accounts**

![Graph showing 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.

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.

**B.2 Compustat**

For the decomposition in section 4 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 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.

In equation 15 we use two different versions of cash flows growth. First we use sales growth, which has the least missing values, defining

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

(B.1)

Second, we use earnings growth scaled by assets as follows

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

(B.2)

B.3 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

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

(B.3)

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

(B.4)

$$
\hat{\sigma}_{\varepsilon,s,p} = Median \{ \hat{\sigma}_{\varepsilon,s,p,i} \}_{i \in s}
$$

(B.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 \( s \).

B.4 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 products
4. Compute novelty

B.4.1 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 most-comprehensive 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 hired research assistants to read Investopedia articles and find the best match.

The raw data consist on 1240 unique names of financial products, and for 322 products we find a unique article that exactly matches the financial product SDC description. For the remaining, their representative document consists of a combination of multiple Investopedia articles (2-3 articles). At the end, we utilize a total of 352 distinct Investopedia articles.

Within the Investopedia article, we selected the body text by filtering the relevant sections.

B.4.2 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. We adjust the weights of each term according to the term-frequency-inverse-document-frequency sublinear transformation and normalize the vectors to unit length.

i) Parsing Methods

We use 1-grams and 2-grams (single words and two-word phrases) as tokens. In general one could use n-grams, meaning distinct n-length phrases. For the types of documents we are interested in, however, meaningful and irreducible phrases having 3 or more words are
quite rare. Also note that we will use the terms “word”, “term”, and “token” interchangeably
and these will refer to the set of 1-grams and 2-grams in all cases.

ii) Lemmatizer Methods

We use WordNetLemmatizer provided as part of the NLTK Python module (nltk.org),
which utilizes the WordNet lexical database (wordnet.princeton.edu), to reduce words to
their root forms by removing conjugations like plural suffixes (Fellbaum, 2010). For instance,
the word “compounds” would be mapped to “compound”.

iii) Word Vector Normalization

The text documents are first converted into term vectors that indicate, for each term,
how many times the term appears in a document. Each document vector is of length \( M \),
which is the number of terms that we include in our vocabulary. The corpus of documents
can then be represented by a very sparse matrix of term counts with elements \( c_{km} \), where
\( k \in \{1, \ldots, K\} = \mathcal{K} \) represents the document (patent or a product category) and \( m \in \{1, \ldots, M\} = \mathcal{M} \) represents the term.

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

\[
\log \left( \frac{K + 1}{d_m + 1} \right) + 1 \quad \text{where } \quad d_m = |\{k \in \mathcal{K}|c_{km} > 0\}|
\]

Thus if a word appears in all documents, it is assigned a weight of one, while those appearing
in fewer documents get larger weights, and this relationship is sublinear. For our weighting
scheme, we use document frequencies from the patent data, as that corpus is considerably
larger and less prone to noise.

Finally, we are left with a weighted, \( \ell^2 \)-normalized word frequency vector \( f_k \) for each
document \( k \) with elements

\[
f_{km} = \frac{w_m c_{km}}{\sqrt{\sum_{m'} (w_m c_{km'})^2}}
\]

B.5 Compute similarity score between products

We used three distinct methods to measure similarity 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. In Appendix B.4 we provide a technical description of the procedure and statistics of the dissimilarity scores.

Our measures of novelty is built using methods from natural language processing using the following steps

C 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.

C.1 Framework for Variance Decompositions

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

\[ Y_j \equiv X_{1j} + X_{2j} \quad (C.1) \]

The variance of \( Y \) is given by

\[ Var(Y_j) = Var(X_{1j}) + Var(X_{2j}) + 2Cov(X_{1j}, X_{2j}) \quad (C.2) \]

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

\[ X_{1j} = \beta_{10} + \beta_1 Y_j + \nu_{1j} \]
\[ X_{2j} = \beta_{20} + \beta_1 Y_j + \nu_{2j} \]
where the estimated OLS coefficients are given by the following

\[
\hat{\beta}_1 = \frac{\text{Cov}(X_{1j}, Y_j)}{\text{Var}(Y_j)} = \frac{\text{Var}(X_{1j}) + \text{Cov}(X_{1j}, X_{2j})}{\text{Var}(Y_j)}
\]

\[
\hat{\beta}_2 = \frac{\text{Cov}(X_{2j}, Y_j)}{\text{Var}(Y_j)} = \frac{\text{Var}(X_{2j}) + \text{Cov}(X_{1j}, X_{2j})}{\text{Var}(Y_j)}
\]

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

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

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.

### C.2 Proof of proposed decomposition

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

\[
\log Y_{st} = 2 \log \left[ \frac{\sum_{i \in I_{ist}} \chi_{ist}}{I_{st}} \right] + \log \left[ \frac{\sum_{i \in I_{ist}} \omega_{ist} \Lambda_{ist}}{\sum_{i \in I_{ist}} \omega_{ist} (1 - \Lambda_{ist})} \right]^2 + \log \left( \frac{1}{\sigma_{st}^2 + \sigma_{e,st}^2} \right) + \log \left[ \frac{\eta_{ist}}{\gamma} \right] \tag{C.3}
\]

where the investors demand component can be re-written as \( \log \eta_{ist} - \log \gamma \). The first term in the demand component is assumed to be \( \log \eta_{ist} = \log \eta_s + \log \psi_t \) (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.

\[
\Delta^{s,t} \log Y_{st} = \left( \log(Y_{st}) - \log(Y_s) \right) - \left( \log(Y_{st}) - \log(Y_s) \right) \tag{C.4}
\]

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

\[
\Delta^{s,t} X_{1st} = \left( X_{1st} - \bar{X}_{1s} \right) - \left( X_{1st} - \bar{X}_{1s} \right) = 0 \tag{C.5}
\]
And thus, we have that double differences in proceeds are a function of the productivity of proceeds and a component capturing market power and risk.

\[
\Delta^{s,t} \log Y_{st} = \Delta^{s,t} 2 \log \left[ \frac{\sum_{i \in I_{st}} \chi_{it}}{I_{st}} \right] + \Delta^{s,t} \left[ \log \left( \frac{\sum_{i \in I_{st}} \frac{\omega_{ist}}{L_{ist}} \Lambda_{ist}}{\sum_{i \in I_{st}} \omega_{ist} (1 - \Lambda_{ist})} \right)^2 + \log \left( \frac{1}{\sigma_{st}^2 + \sigma_{\varepsilon, st}^2} \right) \right] 
\]

(C.6)

C.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

\[
Y_j = \Delta^{s,t} \log Y_{st} \\
X_{1j} = \Delta^{s,t} 2 \log \left[ \frac{\sum_{i \in I_{st}} \chi_{it}}{I_{st}} \right] \\
X_{2j} = \Delta^{s,t} \left[ \log \left( \frac{\sum_{i \in I_{st}} \frac{\omega_{ist}}{L_{ist}} \Lambda_{ist}}{\sum_{i \in I_{st}} \omega_{ist} (1 - \Lambda_{ist})} \right)^2 + \log \left( \frac{1}{\sigma_{st}^2 + \sigma_{\varepsilon, st}^2} \right) \right] 
\]

D Supplemental Results

We decompose total proceeds into the number of issuances and proceeds per issuance (right panel of Figure 10). Over the entire period, firms are more likely to use old types of securities, but the number of issuances of new issuances is growing over time, while the number of issuances of old security types declining at fast pace. The average proceeds per issuance is growing over time, and the pace of growth is particularly large among new security types.

D.1 Association between proceeds and types of securities

Sectors’ ability to increase the amount of external finance through security issuance varies by sector. We evaluate how the evolution of proceeds across sectors is correlated with the
Figure 9: 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.

Table 7: Statistics on Components: Robustness

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>(\Delta s,t \Delta Y_{st} )</th>
<th>(\Delta s,t \Delta \bar{\chi} )</th>
<th>(\Delta s,t \Delta Z )</th>
<th>(\Delta s,t \Delta L )</th>
<th>(\Delta s,t \Delta I )</th>
<th>(\Delta s,t \Delta CV_{\chi} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proceeds</td>
<td>0.00</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>productivity</td>
<td>0.00</td>
<td>0.73</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market power and risk</td>
<td>0.00</td>
<td>0.52</td>
<td>-0.21</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number Issuers</td>
<td>0.00</td>
<td>0.19</td>
<td>-0.00</td>
<td>0.27</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number Types</td>
<td>0.00</td>
<td>0.37</td>
<td>0.06</td>
<td>0.46</td>
<td>0.57</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Coefficient Variation</td>
<td>0.00</td>
<td>0.04</td>
<td>-0.01</td>
<td>0.07</td>
<td>0.48</td>
<td>0.14</td>
<td>1</td>
</tr>
</tbody>
</table>

types of securities issued by estimating

\[
\Delta \log Y_{s,t} = \beta X_{s,t} + \alpha_s + \gamma_t + \varepsilon_{s,t} \tag{D.1}
\]

where \(\Delta \log Y_{s,t} \) is the change in log proceeds of sector \(s\) in period \(t\), and \(X_{s,t}\) are variables capturing various characteristics of security types used by the sector. We control for sector and time fixed effects to account for systematic differences in growth rate over time and
across sectors. We construct variables capturing the importance of new security types (share of new types, novelty of new types, and average age of types), the association of those types with the sector (average of dummy indicating sector is main sector, and average ranking of the sector within type).
Table 8: Allocation of Securities to Sectors

<table>
<thead>
<tr>
<th></th>
<th>(1) New Types (share)</th>
<th>(2) Novelty (average)</th>
<th>(3) Age Types (share)</th>
<th>(4) Main Sector Rank Sector (average)</th>
<th>(5) Rank Sector (average)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_x$</td>
<td>0.964*** (0.125)</td>
<td>0.258*** (0.068)</td>
<td>-0.029*** (0.003)</td>
<td>0.380*** (0.135)</td>
<td>-0.023*** (0.003)</td>
</tr>
<tr>
<td>Observations</td>
<td>2,363</td>
<td>2,000</td>
<td>2,363</td>
<td>2,363</td>
<td>2,363</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.243</td>
<td>0.231</td>
<td>0.257</td>
<td>0.226</td>
<td>0.241</td>
</tr>
<tr>
<td>Sector</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Time</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
</tbody>
</table>

Notes: The table shows the regression output from regressing equation D.1 for changes in proceeds by sector $i$ in period $t$ relative to period $t - 1$. Each column consist in running the regression on distinct independent variables defined at the sector-period level: Column (1) uses the share of new security types; column (2) uses the share of new security types weighted by their novelty; column (3) uses the average age of security types; column (4) uses the share of security types whose main sector (rank 1 and rank 2) is sector $i$; column (5) uses the average ranking of the sector within the security type. The regressions use the baseline dataset with sectors defined at 4-digit SIC codes.

Table 8 shows that sectors that there is an association between innovation and growth in proceeds. Sectors that use relatively more new types of securities and more novel, are more likely to growth at faster pace (column 1-2). Indeed sectors that use on average older securities types exhibit slower growth (column 3). There is also an positive association between using sector specific types and growth in proceeds, which suggests that issuers that are able to use financial contracts that are best suited for their type of activity may allow them to obtain more capital using securities, as opposed of other sources of funding.

D.2 Concentration of security usage by sectors

As a measure of market concentration we calculate the Hirsch-Herfindahl Index (HHI) for each sector based on financial products between 25th and 75th percentile in terms of popularity. Figure 12 shows that the index is between 0.58 and 1 and the average HHI is 0.82, providing further support to our assumption that firms have market power when they issue securities.

We use for this exercise only the securities that are in the middle of the popularity spectrum to avoid our results being driven by extremely popular securities or by securities used only once or twice.
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.