

Private Debt Financing and Product Market Expansion*

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Abstract

This paper investigates how access to private debt (PD) financing supports product market expansion among manufacturers of consumer goods. Combining loan-level data with product-level sales, the evidence shows that during PD loan tenure, firms experience increased revenues driven by newly introduced products—both in existing and new product lines—and expansion into new geographic markets through entry into retail stores in previously unserved counties. While bank-only financing also increases revenues, PD is uniquely associated with these expansion strategies. Industry expertise and greater managerial support emerge as key mechanisms, highlighting the role of PD as a strategic partner rather than a passive financier. Our detailed data allow controlling for confounding factors such as access to bank financing and the presence of private equity intermediaries. These findings inform regulatory debates by demonstrating that private credit supports innovation and economic dynamism, despite concerns about market opacity and liquidity risk.

KEYWORDS: PRIVATE DEBT, PRODUCT MARKET, INNOVATION, NON-PRICE COMPETITION, MIDDLE MARKET

JEL CLASSIFICATION: G23, G30, L15, L25, O31, O32

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1 Introduction

Private debt (PD) has fundamentally reshaped corporate financing since the 2008 financial crisis, evolving from a niche market into a major alternative to traditional bank financing. Its success is largely attributed to regulatory constraints on banks' ability to engage in high-risk lending, particularly for private equity deals and direct loans to middle-market firms.¹ The expansion of private credit has sparked considerable regulatory debate. Unlike public debt markets, which are heavily regulated to ensure transparency and oversight, PD remains largely opaque to this day. While private credit general partners argue that the loans they arrange are safe and that underwriting standards are high, regulators have expressed concerns about valuation practices, fees, and potential conflicts of interest.²

Despite the controversy surrounding private creditors, they fill important financing gaps for firms lacking access to traditional credit (Davydiuk et al., 2024b). While recent research examines how private debt interacts with traditional bank debt (Haque et al., 2025), less is known about potential synergies between the PD business model and firms' product market strategies. This paper provides the first systematic evidence on private debt's interaction with product innovation and geographic expansion, focusing on consumer goods manufacturers. These companies present a compelling setting for studying PD's role in corporate strategy, as they rely on continued credit to innovate and compete for profits (Granja and Moreira, 2022; Argente et al., 2024), require substantial capital for product development cycles, and face intense competitive pressure from rival brands at retailers. These challenges align with private credit's potential advantages in providing flexible financing and strategic support.

To capture the interactions between private credit and product market dynamics, we leverage a unique dataset that combines loan-level information for consumer goods manufacturers with granular product-level sales at U.S. retailers. This comprehensive data allows us to precisely track product introduction and geographic expansion through retail entry. We combine stacked cohort differences-in-differences (DID) specifications with careful matching procedures designed

¹See the February 2024 article "What Private Credit Is Booming and Banks Are Fighting Back", available at <https://www.bloomberg.com>

²"I'm concerned about valuation issues: how they're marking these investments because they are illiquid. I'm concerned about—as we would be with other private funds—fee and expense issues, and with conflict-of-interest issues. I think what we have to do from our perspective is to make sure that folks are not abusing the lack of transparency." – Gurbir Grewal, former SEC Director.

to isolate the presence of private lenders while controlling for confounding factors such as access to bank financing, private equity involvement, and firms' risk profile.

Our analysis reveals distinctive patterns between firms financed by private debt and those financed solely by traditional banks. During the tenure of PD loans, companies experience increased sales that coincide with both the expansion of existing product lines and the introduction of new ones. Additionally, these firms expand geographically, with new sales stemming from entry into stores in previously unserved counties. While both bank and PD financing are associated with revenue growth, only private debt financing shows these specific expansion patterns. In contrast, firms with bank-only financing experience sales growth that originates primarily from existing products and established store networks. These results suggest that private creditors provide strategic financing to firms pursuing dual growth strategies—strengthening their current market position while simultaneously expanding into new product segments and geographic markets.³

Banks and private lenders might select firms based on distinct debt instruments whose underlying structure correlates with product market performance. For instance, firms without access to traditional bank financing are inherently smaller and riskier and might rely on PD for business development (Davydiuk et al., 2024b). Similarly, deals intermediated by private equity (PE) companies, which increasingly involve private creditors, bring their own benefits to target firms (Boucly et al., 2011; Fracassi et al., 2022), making it hard to disentangle the effects of PD and PE involvement. Leveraging the richness of our loan-level data, we isolate the effect of private lender involvement in firms' creditor mix while controlling for these likely confounding factors. In a more restrictive procedure, we compare firms financed by both banks and private debt lenders to other firms *that closed a deal of the same class (either direct debt or PE-intermediated) in the same month but financed solely by banks.*⁴ We show that our results are robust to this empirical design, even if we restrict the deals to LBOs only. This approach ensures that our baseline results are not driven by differences in access to capital markets, deal timing, or PE involvement.

³The SCIO Automation case study provides a concrete example of this mechanism. Partners Group's financing package supported the company's strategy to expand and enhance its products and services in new markets. See [SCIO Automation – Case Study](#).

⁴We take only the first deal of each class for both treated and control firms in the match. In a robustness exercise, we restrict the matching sample to the first deal ever. The results are qualitatively similar.

To understand the mechanisms underlying our results, we examine heterogeneity across lender and borrower characteristics. We find that expansion patterns are stronger when private debt providers have industry expertise in the borrower's sector and greater capacity for active monitoring and managerial support (proxied by smaller funds managing fewer deals (Davydiuk et al., 2024b)). Importantly, we rule out that our main findings stem from synergies between bank and private debt financing. When we reverse our analysis and create the control group with firms financed only by PD, we find mostly insignificant effects on product innovation or geographic expansion, particularly when accounting for selection by focusing on control firms with better access to traditional bank financing.⁵ Similarly, we find no evidence that the effects vary with borrower financial constraints, suggesting that our results do not reflect simply the provision of additional capital by private lenders. While competing explanations cannot be completely ruled out given the complexity of credit markets, our collective evidence implies that the involvement of private lenders brings strategic aspects that are meaningful for product market expansion, while traditional banks offer a more conservative financing that generates revenues from existing operations.

Within the regulatory scrutiny surrounding PD's role as an emerging source of financing, one major concern is the close relationship between private equity firms and private debt providers, with private credit now financing the vast majority of private equity deals (Block et al., 2024). This strong interconnection may increase systemic risk, as a shock to the private equity sector could spill over into the private credit market. Additional risks stem from the illiquidity of private credit and the potential consequences of a recession, which could make it difficult for investors to exit their positions. Moreover, increased competition with banks and substantial dry powder in the market could pressure private debt lenders to lower their lending standards.⁶

While these are valid concerns, private lenders have filled an important gap by providing capital to companies that might otherwise struggle to access traditional financing. In the consumer goods sector, where credit is essential for firms' product development and pricing strategies (Kim, 2020; Kabir,

⁵Specifically, larger firms and those with lower sensitivity to industry-wide revenue fluctuations (lower "beta", as in Acharya et al. (2013)), thus being less risky.

⁶"Private Credit, Bank Rivalry Spurs 'Race to the Bottom,' Moody's Says". September 2023, available at <https://www.bloomberg.com>

2021; Granja and Moreira, 2022), private lenders often offer faster deal execution, greater structural flexibility, and a higher tolerance for borrower risk—features that may be particularly valuable for firms pursuing time-sensitive innovation and market growth strategies. At the same time, product innovation is a key driver of competitive advantage in industries with rapid technological change and evolving consumer preferences, while maintaining reasonable leverage remains crucial for sustaining a strong product-market position (Campello, 2006; Frésard, 2010). Understanding whether and how private credit relates to product-market outcomes is therefore essential for evaluating the net benefits of this growing financing channel and informing regulatory policy.

By documenting the strategic financing role of private credit in product markets, we contribute to the ongoing regulatory debate. Our evidence shows that private credit can support innovation and economic dynamism despite concerns about market opacity and excessive risk-taking. This raises important questions about the trade-offs in regulating this market: restrictions that limit private debt may also constrain strategic financing options for firms seeking to pursue innovation-intensive market expansion. Our findings suggest that private debt enables product market strategies that traditional bank financing does not support, which informs the regulatory balance between oversight and preserving access to alternative financing.

Related literature: Our paper contributes primarily to two strands of the literature. First, we add to the growing body of research on PD and nonbank lenders. Erel and Inozemtsev (2024) document the rising presence of nonbank financial institutions in the loan and bond markets and highlight key differences between these lenders and traditional banks. Block et al. (2024) provide a comprehensive overview of the PD market based on a survey of general partners, showing that PD funds often rely on private equity-sponsored deals and finance middle-market firms that banks typically avoid due to limited transparency and the absence of tangible assets. In a similar vein, Davydiuk et al. (2024b) emphasize the role of Business Development Companies (BDCs) as substitutes for bank financing. Davydiuk et al. (2024a) further show that BDCs acting as dual holders benefit from superior information flows and governance tools. These advantages enhance monitoring, reduce credit risk, and ultimately lower borrowing costs for portfolio firms despite higher spreads. Jang (2023) find that direct lenders actively monitor borrowers and restructure loans in ways comparable to banks, using detailed data from pri-

vate equity buyouts. [Haque et al. \(2025\)](#) explore firms borrowing simultaneously from banks and PD lenders, finding that PD loans tend to be larger, riskier, more junior, and carry higher spreads and longer maturities. [Erel et al. \(2024\)](#) analyze fund performance and report that PD funds yield statistically insignificant abnormal returns after fees. We extend this literature by examining detailed product-market outcomes, moving beyond loan structure and fund performance to study how private debt financing relates to firms' real operational decisions, with direct implications for end-consumers.

Second, we contribute to the literature on the intersection of credit markets and product market outcomes. A rich body of work shows that credit conditions significantly influence firm innovation and strategic decisions ([Nanda and Nicholas, 2014](#); [Paravisini et al., 2014](#); [Bircan and De Haas, 2019](#); [Friedrich and Zator, 2023](#)). Several studies highlight banks' pivotal role in financing innovation ([Nanda and Nicholas, 2014](#); [Hochberg et al., 2018](#); [Mann, 2018](#)) and demonstrate that financial shocks can suppress R&D ([Bolton et al., 2011, 2013](#); [Doerr, 2021](#)). Our paper relates particularly to [Granja and Moreira \(2022\)](#), who show that credit disruptions during the Global Financial Crisis led to declines in product novelty and success. In addition, [Kim \(2020\)](#) provides evidence that credit-constrained firms change pricing policies to conduct fire sales and liquidate inventories. More generally, our paper relates to the rich literature on the intersection of product markets and corporate finance, which has particularly benefited from the introduction of granular retail data.⁷

We extend this line of research by examining the post-crisis emergence of private debt, showing that not only credit access but also the source of financing is associated with distinct product market patterns. Finally, our findings intersect with research on private equity's impact on firms' non-price competition, such as product expansion and geographic growth ([Fracassi et al., 2022](#)). While prior research emphasizes the benefits of private equity ownership ([Boucly et al., 2011](#)), alongside strategic support from institutional investors ([Fracassi et al., 2022](#)), the impact of private debt remains understudied. We provide novel evidence that private debt financing is associated with product market growth strategies despite creditors facing fundamentally different incentives than equity holders.

⁷See ([Frésard and Phillips, 2022](#)) for a detailed review of the literature, and [Argente et al. \(2017\)](#); [Hajda and Nikolov \(2022\)](#); [Bhattacharya et al. \(2023\)](#) for recent research using retail data.

The paper proceeds as follows: [Section 2](#) provides background on the private debt market. [Section 3](#) describes the data sources and variable construction, presents the matching procedure and summary statistics, and discusses the empirical specifications. Sections [4](#) through [6](#) present our main results and robustness checks. Finally, [Section 7](#) concludes.

2 Market Overview

The global private debt market has expanded significantly in recent years, reaching approximately \$1.7 trillion in 2024, and is projected to grow to \$2.64 trillion by 2029.⁸ The success of private credit is attributed to regulatory measures such as leverage caps, higher capital requirements, and the Volcker Rule's limits on risk-taking, which have reduced banks' ability and incentive to engage in high-risk lending associated with leveraged buyout deals and direct lending to middle-market firms. These regulatory constraints created a gap in the market that private debt lenders quickly filled. Regulatory requirements are not the only factor driving private credit growth; another significant element is the flexibility private credit providers can offer compared to traditional banks. This flexibility can range from customized loan terms to more lenient covenants, making private debt an attractive option for firms that need tailored financing solutions.

In the context of PD lending growth, consumer goods manufacturers are particularly prone to benefit, for having precisely the profile of firms that PD specialize in. Many of these companies are growing middle-market firms that rely on continued credit. In addition, their cash flows depend on continued innovation as existing products lose appeal during their life cycle, facing competition from newer products by rival brands ([Argente et al., 2024](#)). As such, consumer goods firms can grow from both the capital injection—alleviating financing constraints—and from the expertise in the industry provided by PD investors. Indeed, consistent with the overall trends reported in [Block et al. \(2024\)](#), private debt has quickly become one of the primary sources of financing in the consumer products sector. [Figure 1](#) depicts the participation of private lenders among private equity and pure debt deals with consumer goods firms from 2006 to 2023, thus covering our main sample period. As of 2023, almost 60% of PE deals were financed by at least one private debt provider following a clear upward

⁸Preqin, Future of Alternatives 2029 Report. As of December 2024.

trend since 2013, when participation was virtually zero. Similarly, in direct lending, there has been a gradual increase in the share of deals funded by at least one private debt provider, going from just over 20% in 2013 to roughly 70% of deals in 2023.

Insert Figure 1 here

Overall, Figure 1 shows that the consumer goods sector is no exception to the penetration of private credit in corporate financing. In addition, our Nielsen sample period covers the whole post-global financial crisis period—which marked the emergence of PD as an important source of capital (Haque et al., 2025). The relevance of PD financing in this period, together with the granularity of retail data allows us to precisely trace the market expansion of consumer products manufacturers due to the involvement of private lenders.

3 Empirical Strategy

3.1 Data

3.1.1 Private Debt

Data on PD deals come from PitchBook, which provides detailed information on transactions including company characteristics, loan terms, and the class of deal—whether it is direct lending or intermediated by a PE company.⁹ As in Haque et al. (2025), we define private debt as corporate loans extended by non-bank lenders, primarily business development companies (BDCs) and private debt funds. Private debt lenders are identified in PitchBook under the ‘Lender’ category.¹⁰ We consider only transactions denominated in US dollars for companies headquartered in the United States that are manufacturers of consumer goods present in the Nielsen Retail Scanner dataset.

⁹Direct lending refers to loans that are bilaterally negotiated between a borrower and a private debt fund, with the expectation that the lender will hold the loan until maturity (Block et al., 2024). Most PE-intermediated deals consist primarily of direct loans provided to private equity firms for middle-market buyouts (Jang, 2023).

¹⁰To ensure that the lender’s core business aligns with typical private debt activity, we further restrict our sample to entities whose primary business classification falls under one of the following categories: Lender/Debt Provider, Mezzanine, Asset Manager, or PE/Buyout, which together account for 95% of our sample. The remaining 5% of lenders are classified as Growth/Expansion, Hedge Fund, PE-Backed Company, Venture Capital, or Real Estate. These entities occasionally participate in private debt transactions and are therefore retained in the sample.

Figure 2 reports the leading private debt lenders in the consumer product sector, which are consistent with those highlighted in Haque et al. (2025) for the overall market. The initial matched dataset consists of 5,475 deals, of which 35% involve at least one private debt provider; among these, 55% involve only one private lender. Approximately 15% of the deals are PE transactions, and 82% are general debt loans. Among PE deals, 70% are financed by at least one private debt provider, while 30% of debt deals include at least one private credit provider. In terms of facility type, 62% of the deals are term loans, 22% are bonds, and 15% are credit lines. Among facilities involving private debt, 75% are term loans, 19% are credit lines, and only 6% are bonds. The median deal size of debt deals involving private credit is \$40 million, while for PE deals it is \$286 million.

Insert Figure 2 here

3.1.2 Nielsen Retail Scanner

Our analysis utilizes product market data from the NielsenIQ Retail Scanner database, provided through the Kilts Center for Marketing Data Center at the University of Chicago Booth School of Business. This extensive dataset reports information on product-level sales recorded by scanners at participating retail stores throughout the U.S. Weekly, each individual store reports sales data for any product with recorded sales during the week, including number of units sold and weighted average unit price. The original data covers sales of almost 10 million products in 30,000-50,000 stores from approximately 90 retail chains in more than 2,700 counties, thus providing an accurate picture of consumer product markets in the U.S. (Argente et al., 2017, 2024). Our NielsenIQ sample covers sales between January 2006 and December 2023.

The NielsenIQ data employs a hierarchical classification system of products. At the most granular level is the individual product, identified by its Universal Product Code (UPC). These products are organized into approximately 1,100 modules, which represent the most specific product categories and are comparable to 10-digit NAICS classifications (Granja and Moreira, 2022). Modules are further aggregated into 125 product groups, which are then organized into 10 departments representing the broadest product categories. For instance, a particular boxed

whipping cream—identified by its UPC—belongs to the “Whipping Cream” product module, “Cottage Cheese, Sour Cream, Toppings” group, and “Dairy” department.¹¹

To map each UPC to its manufacturer, we supplement our data with information from GS1 U.S. Data Hub. As the official organization responsible for issuing and managing UPCs, GS1 requires any producer seeking barcodes for their products to purchase a company prefix and register their name and address. This prefix, a five- to ten-digit number appearing at the beginning of any UPC belonging to that firm, allows us to identify the parent company of products in the NielsenIQ dataset. Using a comprehensive list of prefixes issued by GS1, we successfully match about 78% of all UPCs in the retail scanner data to their respective manufacturer names. Following this procedure, we build comprehensive firm-level product portfolios that we can track across different locations or aggregate to form firm-level product market performance variables.

Finally, we match our Nielsen-GS1 dataset to PitchBook deals by firm names. We follow the string matching algorithm of Schoenle (2017), also used by Argente et al. (2017) and manually check the matches to discard likely false positives. Our final dataset consists of roughly 4.5 million firm-month observations of over 49 thousand firms, out of which 1,907 report at least one deal in the PitchBook dataset.

3.2 Variable Definitions

3.2.1 Active Loans

Our main firm-month independent variables are indicators of outstanding loans based on PitchBook lender and maturity information. *ActiveLender* takes the value of one if there is *at least* one deal of any type outstanding in a given month.¹² Therefore, we restrict our PitchBook sample to deals with reported maturity. We consider the presence of bank and PD loans separately as follows. *ActiveBank* is an indicator that takes the value of one during the tenure of a bank loan, and *ActivePrivate* is defined

¹¹This hierarchical structure was discontinued in 2021. However, NielsenIQ still reports the old categories for all UPCs, allowing the researcher to manually classify products and maintain consistency with the latest data releases.

¹²That is, if a loan is rolled over after maturity or if a loan matures but there are other outstanding loans at the same time, *ActiveLender* remains equal to one.

analogously for deals with private lenders. Since firms can have outstanding loans with multiple types of lenders simultaneously, *ActiveBank* and *ActivePrivate* are not mutually exclusive.

3.2.2 Product Market

First, we aggregate weekly data to monthly frequency for computational feasibility and to smooth weekly consumption fluctuations. From raw data, we compute monthly total revenues in U.S. dollars from each product and store. Next, we aggregate data to the firm-month level to compute basic product market performance measures. *Sales* is the total revenue generated by a firm's products across all locations. *Sales growth* is the log difference between total sales in a given month and in the same month of the previous year, in percentage terms. *Number of products* is the count of unique products that a firm produces while *Number of modules* is the count of modules that the firm's products cover. Hence, these two variables measure the size of the firm's product portfolio and its breadth across different product categories. Similarly, *Number of stores* is the count of stores with a firm's product, and *Number of counties* is the count of counties with a firm's products, thus measuring a firm's spatial reach across stores and geographical locations.

In addition to overall performance measures, we also construct measures of product market expansion along the product and location margins. We account for product portfolio expansion and innovation as follows. *Product entry rate* is the ratio of a firm's revenues from new products to its total revenues, in percentage points. To allow time for a new product to be established on the market, we consider a product as new in the first six months with recorded sales. To explicitly account for expansion toward new product lines as opposed to product launches in previously existing product categories, we decompose *Product Entry Rate* into two components of novelty. Following [Granja and Moreira \(2022\)](#), we define *Product Entry Rate (New Modules)* as the ratio of sales of new products that belong to modules for which the firm has never had products before to total sales. We classify a module as new for a particular firm during the first year after its first appearance in the firm's portfolio. Since R&D timing can be heterogeneous even across similar products, such products can reach retailers in a staggered manner even if they belong to a firm's first efforts to enter a new line. Therefore, we allow 12 months before

considering a module as incumbent in a firm’s portfolio. We define *Product Entry Rate (Old Modules)* likewise, based on new products launched by a firm in its incumbent modules.

To account for the location dimension of product market expansion, we build analogous entry measures based on new points of sale and their respective counties. *Store Entry Rate* is the ratio of sales of a firm’s products in stores where it did not sell products before (“new” stores) to its total revenues. We consider a store as “new” for a firm in the first six months with recorded sales of products from that firm. We also decompose *Store Entry Rate* into two components. *Store Entry Rate (New Counties)* is the ratio of sales in new stores located in counties where the firm did not sell products previously to its total revenues. As with entry in new modules, we consider a county as “new” to a firm during the first 12 months of recorded sales of that firm-county combination. Finally, *Store Entry Rate (Old Counties)* is the ratio of sales in new stores located in counties where the firm already has operations for more than 12 months.¹³ All entry ratios are expressed in percentage points.

3.3 Matching Procedure

To alleviate valid concerns that loan-taking and loan types are endogenous to the firm’s financial situation and its product market prospects, we perform a number of matching approaches exploring the richness of our PitchBook and NielsenIQ data. In all cases, we match each “treated” unit (a firm or a firm-deal) to a single control based on sales, sales growth, number of products, number of modules, number of stores, and number of counties following the procedure by [Fracassi et al. \(2022\)](#). Specifically, for each matching variable, we compute standardized differences between the treated firm and the pool of controls in the month prior to the deal of interest. First, we scale each matching variable by its sample standard deviation. Next, we compute the absolute value of pairwise standardized differences between the treated unit and each possible control. Finally, we sum distances across variables to get pairwise Manhattan distances measure and match each treated unit to its closest control. Our choices of benchmark variables ensure that we match each focal unit to peers as similar as possible in size, recent product market performance, product portfolio size and geographic breadth.

¹³Our results are qualitatively robust to different buffer periods of “newness,” e.g., considering a product or a firm-store as new only in the month where it first appears in the data.

3.3.1 Full sample matching

To form our baseline sample, we match firms with deals from PitchBook to firms from our overall Nielsen-GS1 dataset without any deals during our sample period. First, we restrict our sample of deals to the first loan of any type taken by each PitchBook firm to avoid confounders related to multiple deals and rollovers. We further restrict to firms with non-missing values of all matching variables. We also discard deals closed in 2023 to allow a sizable post-deal estimation period. Following this procedure, we match 999 PitchBook firms to control firms in the month prior to the firm’s first deal.¹⁴ Finally, we exclude post-maturity observations for each firm pair if the loan is not rolled over and no new loan is taken, resulting in a final sample of 288,234 firm-month observations.¹⁵

3.3.2 Deal-level matching

In our second matching approach, we leverage the comprehensiveness of the PitchBook data to alleviate endogeneity issues in comparing firms with outstanding loans to those that never obtained such loans during our sample period. Here, the focus is only on firms with reported loans closed during our sample period to isolate the presence of a private lender while controlling for bank presence in the mix of lenders.

First, we take the first loan of each deal class (direct debt or PE-intermediated) for each firm that has both banks and private lenders in the facility.¹⁶ Next, for each such firm-deal, we form a pool of potential controls that closed their *first deal of the same class at the same month*, but with only banks as lenders. Finally, we select the match that is closest based on our product market matching method described above. Naturally, this stricter procedure results in a much smaller sample consisting of 79 treated units matched to their respective controls, of which 45 involve direct debt deals and 34 had

¹⁴We show the distribution of matched deals across years in [Figure IA.1](#). While there are numerous matched deals every year, roughly one third of the loans were made in 2020 likely to support firms during the COVID-19 pandemic. There are no matched deals in 2006 because *Sales growth* requires at least 12 prior months to be computed.

¹⁵This ensures that within each firm pair, we have only two periods: the pre-deal months and the subsequent period when any loan deal is active (*ActiveLender* = 1).

¹⁶Therefore, treatment is defined at the firm-deal class level, allowing a single firm to enter more than one cohort as “treated” if it takes loans of both classes. We show that our results are robust to restricting to the first deal ever in [Section 6.2](#).

the participation of PE firms.¹⁷ Finally, to build our final sample, we keep only post-deal observations in which both firms in a pair have their respective deals outstanding. Here, for deals with missing maturity, we impute the average maturity of the debt category class¹⁸ to ensure a sizable sample, forming a panel of 22,041 firm-month observations.

3.4 Descriptive Statistics

Summary statistics of our baseline sample are reported in [Table 1](#). Panel A summarizes our full matched sample. Overall, our matching variables of firm’s operational breadth are substantially right-skewed.¹⁹ For instance, while the median firm in our sample sells less than 60 thousand dollars each month, the average firm sells roughly 1.4 million. Number of products, modules, stores, and counties show similar patterns. Overall, entry rates tend to be low as product launches and entry into new stores do not happen very frequently. Naturally, new products in old modules account for most of the entry rate, with only 16% of the overall product entry rate coming from new lines. In contrast, store entry rate is more balanced between new and old counties, with 57% and 43% coming from new points of sale in new and old counties, respectively. On average, 17% of the firm-month observations in our full matched sample have an active lender. In addition, 13% and 6% have an active bank and private lender, respectively. Consequently, only 1% of firm-months have loans outstanding with both banks and private lenders simultaneously.

Insert [Table 1](#) here

Panel B of [Table 1](#) reports the descriptive statistics of the matching variables for firms with PitchBook deals and their controls separately, at the month of the match. The last column reports p -values of t -tests for mean differences between the groups. We find no statistically significant differences across groups for any variable, this ensuring the quality of our matching approach.

¹⁷Figure IA.2 shows a histogram of the distribution of the matched deals over years. Besides 2008 and 2009, all years record at least one of our treated firm-deals. In addition, most years record both direct debt and PE-intermediated loans, ensuring that our sample of matched deals has a good coverage across years and loan classes.

¹⁸The overall average tenor for term loans in our sample is 6.14 years. For credit lines, the average tenor is 4.77 years, while for bonds it is 10.84 years

¹⁹Consistent with other papers that utilize NielsenIQ data e.g., [Kim \(2020\)](#); [Granja and Moreira \(2022\)](#); [Argente et al. \(2024\)](#).

3.5 Empirical Specifications

Our main empirical specifications employ stacked cohort differences-in-differences (DIDs) in the matched samples to circumvent estimation issues related to staggered treatments in two-way-fixed effects (TWFE) estimators.²⁰ Specifically, we define each pair of treated-control units as a *cohort* and include cohort-level fixed effects to ensure within-cohort comparisons at each point in time. In all our matching procedures, we ensure that treated units never enter the sample as the control in another cohort. In all specifications, standard errors are two-way clustered at the firm and year-month levels.

3.5.1 Full matched sample

In our sample of firms with outstanding loans benchmarked against firms with no loans described in Section 3.3.1, we estimate two specifications. First, we assess the overall effect of having an active lender as follows:

$$y_{f,c,t} = \beta_l \cdot \text{ActiveLender}_{f,c,t} + \mu_{f,c} + \mu_{t,c} + \epsilon_{f,c,t}, \quad (1)$$

where $y_{f,c,t}$ is either log of total sales or the sales entry rate measures for firm f , month t , and cohort c . $\mu_{f,c}$ and $\mu_{t,c}$ are firm-cohort and time-cohort fixed effects, respectively. The DID coefficient β_l estimates the cross-cohort average change in the dependent variable for the treated firm after the first deal relative to its matched counterfactual.

To identify differentials in product market performance between firms financed by banks or private lenders, we further estimate the following specification:

$$y_{f,c,t} = \beta_p \cdot \text{ActivePrivate}_{f,c,t} + \beta_b \cdot \text{ActiveBank}_{f,c,t} + \mu_{f,c} + \mu_{t,c} + \epsilon_{f,c,t}. \quad (2)$$

where the coefficients of interest β_b and β_p capture changes in the dependent variable driven by active PD and bank loans separately.

²⁰See, e.g., (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Baker et al., 2022).

Finally, to capture dynamic effects and assess pretrends, we estimate event study specifications on the full matched sample. In these tests, we restrict the sample to observations from 12 months before to 24 months after the first deal from each type of lender (any lender, private lender, or bank) for each cohort. Specifically, we estimate the following specification:

$$y_{f,c,t} = \sum_{\substack{j=-12 \\ j \neq -1}}^{24} \beta_j \cdot [ActiveLender_{f,c,t-1} \times \mathbb{1}\{t = j\}] + \mu_{f,c} + \mu_{t,c} + \epsilon_{f,c,t} \quad (3)$$

In [Equation \(3\)](#), the coefficients of interest are β_j , which estimate differences in the outcome variable between firms with active loans and their matched counterfactuals relative to the reference period ($j = -1$). We estimate [Equation \(3\)](#) with *ActiveLender*, *ActivePrivate*, and *ActiveBank* separately as the independent variables. When estimating the dynamic effects for a particular type of lender (private lender or bank), we control for the presence of the other type of lender with an indicator variable as well (*ActiveBank* or *ActivePrivate*). We do so to avoid contamination of the dynamic estimates with changes in the status of loans from the other type of lender.²¹

3.5.2 Deal-level matched sample

In our finer deal-matched sample described in [Section 3.3.2](#), we estimate the following stacked DID model:

$$y_{f,c,t} = \gamma \cdot PrivateDebt_{f,c} \times Post_{t,c} + \mu_{f,c} + \mu_{t,c} + \epsilon_{f,c,t}, \quad (4)$$

where *PrivateDebt*_{*f,c*} is an indicator of the presence of a private lender in the mix of lenders in the deal, and *Post*_{*t,c*} is an indicator of the post-deal, before maturity period.²² Due to the sample construction, the DID coefficient γ estimates the differential effect on the dependent variable of having a private lender *in addition to a bank lender* in the mix of creditors for first deals of similar class closed in the same month. Therefore, estimation of [Equation \(4\)](#) relies solely on variation stemming from the presence of a private lender while controlling for class and timing of the loan as well as access to bank debt, which ensures comparison across firms with similar financial standing.

²¹Our results are qualitatively similar if we do not control for active loans from the other type of lender.

²²The individual coefficients of these indicators cannot be estimated, as they are absorbed by the fixed effects

4 Results

4.1 Baseline

Table 2 reports the results of our baseline model, Equations (1) and (2). Columns (1)-(2) present estimates for total sales, columns (3)-(4) focus on sales from new products, while columns (5)-(6) refer to sales from new stores.²³ Column (1) shows that firms with any active lender, regardless of whether it is a bank or a private debt fund, are associated with 63% higher sales, relative to firms without active lenders. Column (2) examines heterogeneity by lender type. Firms with an active bank relationship are associated with a 41% increase in sales while firms with an active private lender show a 37% increase in sales, with both coefficients statistically significant. These results indicate that both active banks and PD lenders are associated with larger sales, likely due to increases in access to finance, alleviating financial constraints and working capital disruptions. Additionally, such positive performance might also be associated with enhanced monitoring from the lenders, especially banks, and improved by industry expertise provided by private debt lenders, which we investigate further.

Insert Table 2 here

The estimates in columns (1)-(2) of Table 2 provide initial evidence that firms with active loans generate more revenue than their counterparts, either by causal channels such as access to financing, monitoring and expertise, or mere association due to selection of lenders into firms. However, sales effects can reflect multiple underlying product market strategies simultaneously. For instance, larger revenues can come from changes in prices or product availability at the product or location dimensions. To further explore these nuances, columns (3)-(4) focus on the relevance of new products with our measure of sales-weighted product entry rate. In column (3), we find that simply having an active lender of any type is associated with a decrease in the share of sales coming from new products. However, when disaggregating by lender type in column (4), the estimates show that having an active bank relationship is negatively correlated with sales from new products, while firms with an active private debt loan experience approximately 5.19 percentage points higher share of sales

²³In columns (1)-(3) we report $e^{\beta} - 1$ where β is the original estimate from Equations 1 and 2 with the dependent variable in log levels. Standard errors are adjusted accordingly using the Delta method.

from new products. This estimate is economically meaningful, corresponding to roughly 61% of the product entry rate's unconditional sample mean.

Finally, in columns (5)–(6), we examine whether geographic market expansion through entry into new stores is another driver of the observed increase in sales. Column (5) shows that having an active lender is negatively associated with the shares of sales in new stores. Column (6) reveals that this result is primarily driven by firms with active bank loans, consistent with the results with product entry rates in column (4). In contrast, firms with active private debt exhibit significantly higher share of sales from stores newly carrying their products, approximately 1.56 percentage points, which corresponds to 13% of the sample mean.²⁴

Although we match firms based on several observable characteristics, the results in [Table 2](#) do not convey whether the matched firms experience similar trends in the outcome variables before the loans. In particular, while we find no significant differences in the period of the matching, matched firms could be following distinct trajectories, coinciding in the month before the treated firm takes its first loan. In addition, firms that borrow from PD lenders or banks can be markedly different, which could generate pretrends in one of these particular categories. To directly address these concerns and assess the evolution of treatment effects, we estimate the event studies in [Equation \(3\)](#) and report results in [Figure 3](#).

Insert [Figure 3](#) here

Panels A, B, and C of [Figure 3](#) report estimates for sales, product and store entry rates as the dependent variables, respectively. In each panel, the left and right-hand figures reports results with *ActivePrivate* and *ActiveBank* as the independent variables, respectively. In all graphs, we find no statistically significant pretrends, ensuring the quality of our matching procedure. The estimates in Panel A show a positive and steady trend after the first deal with a PD lender which develops across several months. We find similar results for bank lending, although the trends takes even more time to gain momentum. In both cases, the results show that our data and empirical strategy are able to capture effects of firms' access to capital relative to otherwise similar firm's with no recorded deals.

²⁴In [Table IA.1](#), we report results from specifications similar to [Equations \(1\)](#) and [\(2\)](#) where we use the total number of active lenders, active banks, and active private lenders as independent variables, instead of indicators. The results confirm the patterns observed in [Table 2](#).

Panel B of [Figure 3](#) documents a positive and persistent increase in the share of sales from new products following the first deal with a PD lender. Notably, this increase in product entry rates is immediate, materializing in only a few months. As new products take time and several stages from development to launch, these results suggest that many firms already have advanced R&D projects in place, such that access to PD capital coincides with bringing these products to the market. This timing is consistent with strategic financing whereby firms with advanced-stage products match with specialized lenders who are willing to finance the roll out of the new product. In stark contrast, loans from banks are associated with a decline in product entry rate after the deal, although the estimates are not significant and diminish over the months following the deal. Finally, Panel C of [Figure 3](#) reports event study estimates for store entry rates. The results show that firms financed by PD providers experience an increase in revenues coming from new points of sale. Although these results are stronger within the first six months after the deal, entry rates remain positive, showing a continuous but attenuating expansion to new stores. Again, we find no evidence of expansion into new localities due to bank financing, with no visible breaks in the trend around the deals.²⁵

Our baseline results suggest that while both private debt and bank financing are associated with increased revenues, the underlying growth strategies differ substantially. For firms financed by private debt, sales are driven by expansion at both the product and locality margins. While the negative correlation between bank financing and entry rates does not imply that bank-financed firms avoid innovation or expansion, it suggests that their sales growth largely originates from existing products and store networks, reflecting a more conservative approach to growth. This could be driven by several factors related to strategic financing. Unlike banks, PD lenders are more willing to finance firms with high intangible assets, which are typically riskier but more innovation-oriented. In addition, PD deals offer more flexible covenants ([Block et al., 2024](#)), giving firms more freedom in pursuing risky growth projects. Finally, PD lenders, similarly to private equity investors, tend to be more actively involved in firm strategy, as opposed to traditional banks ([Davydiuk et al., 2024b](#)).

²⁵For completeness, [Figure IA.4](#) reports estimates for event studies considering deals any type of lenders. With the exception of sales, reported in Panel A, the estimates show no clear responses when lender types are disregarded, consistent with our results in [Figure 3](#).

Although our baseline results reveal distinct post-deal expansion trajectories between PD- and bank-financed firms, these estimates may be confounded by factors related to access to traditional financing and PE involvement. For instance, the observed relationship may be driven by selection rather than a direct impact of private debt on product innovation. PD providers might finance companies that are often intangible-intensive and inherently more innovative, but riskier, thus lacking access to the traditional banking market. Another possibility is that many PD deals involve PE sponsorship, implying that our results could be confounded by PE transactions' positive influence on firm performance (Boucly et al., 2011; Fracassi et al., 2022). Specifically, PE firms might selectively back the most innovative companies and use private debt to finance them. The next section addresses these identification concerns and isolate how PD involvement shapes firms' product market expansion.

4.2 DID

In our deal-matched stacked DID specification, identification relies solely on variation stemming from private debt involvement in a deal. Specifically, the treated groups comprise firm-deals financed by both banks and private debt lenders, while matched counterfactuals consist of similar deals (either direct debt or PE-intermediated) that occurred in the same month and were financed only by banks. Thus, this rule out the possibility that our results are driven by differences in firm types—for example, firms that can access the banking market versus those that cannot. In this setting, both treated and control firms have access to bank financing, but only the treated ones also receive funding from private debt lenders. In addition, by matching within deal type—comparing debt deals with other debt deals and PE deals with other PE deals—we isolate the impact of private debt participation from the potentially confounding influence of PE activity. Otherwise, our findings could be potentially driven by the nature of the deal and we would mistakenly attribute effects of PE involvement to private debt financing.

Here, the focus is on sales entry rates to examine the differential effects of private debt on product-launch strategies and geographic market expansion. To better capture the dimensions of product entry, we split sales from newly launched products between existing and new modules, as defined in our decomposition of the product entry rate in [Section 3.2.2](#). Similarly, for store entry, we distinguish between

the firm's products entering stores in counties where the firm already operates from those opened in entirely new counties where the firm has not previously been active.

Insert Table 3 here

Table 3 reports the estimates from Equation (4), with Panel A examining product entry and Panel B focusing on geographic expansion through store entry. Panel A, Column (1), is consistent with previous findings, showing that firms financed by private debt lenders and banks experience a statistically significant increase in sales from new products following the deal, relative to firms financed solely by banks. Columns (2) and (3) provide a breakdown of sales entry rate between old and new product modules.²⁶ Interestingly, firms that receive financing from both banks and private debt lenders show an increase in sales at both margins, indicating both an expansion of existing product lines and the introduction of new product lines. These results suggest that the presence of private debt helps support a dual-growth strategy in product portfolios, whereby firms maintain their position in existing markets while simultaneously innovating and expanding into new ones.

Panel B extends the analysis to geographic growth. Column (1) shows that firms backed by private debt see increased sales from entry into new stores. Columns (2)-(3) reveal that this effect is entirely driven by entry into new counties rather than growth within locations where the firm already has operations. Overall, the results suggest that private debt equips firms with the capacity to scale more aggressively—fueling growth not just through broader product offerings but also by pushing into untapped geographic markets. Together with the results in Section 4.1, this suggests that, although both banks and private lenders are capable of generating revenues to their borrowers (or to match with growing companies), only private lenders tend to finance product portfolio and geographic growth strategies.²⁷

²⁶Note that the coefficients in columns (2) and (3) add to the coefficient in column (1) due to the exact entry rate decomposition.

²⁷In unreported estimates of Equation (4), we find no significant effects in total sales. These results are available upon request.

5 Channels

5.1 Private Debt as a Strategic Partner

The previous sections provide evidence that private credit fosters firms' product-market expansion, either through the introduction of new products or entry into stores in previously unserved areas. An important question that remains is why this effect arises. One explanation lies in the nature of PD capital itself, which tends to be more flexible than traditional bank financing both in terms of covenant structures and the possibility of renegotiation. Moreover, private credit providers often go beyond simply supplying capital. They can offer managerial support and industry-specific expertise to their portfolio firms, in a way that resembles private equity investors (Davydiuk et al., 2024b). This support can help firms implement strategies more effectively, accelerate product development, or expand into new markets. In this section, we investigate whether such managerial assistance and sector-specific expertise constitute a key strategic mechanism behind the observed product-market expansion.

We proxy managerial assistance using the average size of the funds raised by lenders at a given point in time. The intuition is that larger lenders have more capital to deploy, which typically results in a broader portfolio of companies to oversee. In contrast, smaller funds tend to develop more specialized expertise that can benefit their portfolio firms (Humphery-Jenner, 2012). As a result, the capacity to provide dedicated managerial support to each firm is likely to be lower when lenders operate larger funds, making fund size an inverse measure of hands-on involvement and monitoring. Since deals may involve multiple lenders, we take the average fund size across participating lenders for each deal.²⁸

To capture industry specialization, we first identify the industry in which each lender is most active, defined as the industry in which it has completed the largest number of deals.²⁹ We define industries and NielsenIQ's product "groups", and assign firms to the groups that account for the largest share of total revenues.³⁰ For each deal, we then compute the fraction of lenders that specialize in the borrower's industry, therefore proxying for the degree of sector-specific expertise available to the

²⁸This test is restricted to deals involving at least one private debt fund, as fund size is available only for these lenders.

²⁹We require a minimum threshold of four deals.

³⁰Here, we focus on groups to have a relatively granular definition of industry, but still coarse enough that we observe multiple deals within each industry.

firm. Finally, we construct a specialization dummy equal to one if this fraction is above the sample mean, and zero otherwise. This indicator distinguishes between deals financed by industry-focused lenders *to borrowers at the industry of specialization* and those lenders with more diversified participation or lending to borrowers outside of the lender's industry of expertise.

Insert Table 4 here

Table 4 reports the results of a triple differences specification where we interact our baseline DID model with measures of industry specialization and managerial assistance. Panel A presents the results for product entry. Columns (1) and (2) show that the positive effect on sales from new products is driven by private debt providers that devote greater managerial attention (with a negative effect for larger funds, which provide less individualized support), and firms financed by more specialized funds in the borrower's industry. The results are primarily driven by higher sales from the expansion toward modules, as well as expansion of existing modules. Panel B shows that borrowers financed by funds with greater expertise in the borrower's industry and with stronger capacity to assist and monitor management achieve higher sales from new stores (Columns (1) and (2)), particularly those located in previously unserved counties (Columns (3) and (4)). Our estimates in Column (1) of Panels A and B imply that a 10% increase in the total capital of the average fund for each deal translates into roughly 0.60 p.p. lower product and store entry rates. In addition, Column (2) suggests that funds specialized in the borrower's industry increase product and store entry rates by 9.8 and 11.5 p.p. on average, respectively, relative to non-specialized deals.

Taken together, these results provide evidence that private debt offers more than capital. By combining industry expertise with the ability to monitor and support management, private lenders actively shape firms' product-market strategies. This value-added role sets them apart from banks, and highlights how private credit can operate as both financier and strategic partner in driving firm growth.

5.2 Financial Constraints

An alternative mechanism through which private debt can support product market expansions is by providing capital for growth. We test this idea by examining heterogeneous effects across

two proxies for financial constraints among the treated firms in our sample. First, we rely on the contention by Acharya et al. (2013) that riskier firms face worse contractual terms and higher cost when accessing bank financing via credit lines. As such, access to capital is more restricted to firms that are more sensitive to aggregate risks. Conversely, firms with lower exposure to aggregate risks have easier access to access to bank financing. Second, we follow Fracassi et al. (2022) and use firm size, measured by total revenue, as an additional proxy for financing constraints, since larger firms generally have better access to external capital.

To proxy for a firm's riskiness, we adapt the firm "beta" approach by Acharya et al. (2013) to our NielsenIQ data by estimating a firm's revenue responsiveness to sensitivity to aggregate fluctuations in its broad industry. Specifically, we assign firms to the NielsenIQ department that represents the largest share of their overall revenues in the sample. Next, we estimate firm-level regressions of the log of firms monthly revenues on the log of total revenues in that firm's department. To avoid contaminating these estimates with look-ahead bias from any effects brought by the debt deals, we restrict the sample of these regressions to the the period that precedes each firm's first deal. The resulting coefficient of these regressions, the firms' *revenue betas*, measure the elasticity of firms revenues to total revenues in its broader sector, therefore proxying for firms' exposure to aggregate fluctuations. Next, we classify the cohorts in our exercise based on the beta of the treated firm, assigning *LowBeta* to treated firms below average. We then interact this indicator with *PrivateDebt* to access heterogeneity by treated firm's riskiness. We follow a similar approach to classify treated firms by size. We compute treated firms' total revenue in the month prior to the date of the deal used in the match. Next, we classify these firms as *Large* if they are above the sample mean, and interact this indicator with *PrivateDebt*.

Table 5 presents the results, with Panel A reporting estimates for product entry and Panel B for store entry. The interaction terms show no significant differences in the effect of private debt capital across firms with different likelihoods of obtaining external capital. In other words, firms that were more or less financially constrained appear to benefit similarly from private debt. This is not surprising, as all firms in our baseline specification have access to bank capital by design, suggesting that additional private debt does not further relax financing constraints. In this context, our findings indicate that private debt is not simply a complement to bank capital in easing constraints.

Instead, the product and store market expansions observed among treated firms likely operate through alternative channels, such as managerial support and industry knowledge as evidenced in [Section 5.1](#). This distinction is important because it suggests that private debt can affect firm behavior even in environments where access to traditional bank finance is already available, highlighting synergic mechanisms beyond simple capital provision.

Insert [Table 5](#) here

6 Robustness

6.1 Presence of Banks

Our results in [Section 4.2](#) show that the presence of a private lender on top of banks in firms' portfolio of lenders is associated with product market expansion. While these findings may be driven by private lenders' expertise and closer attention to their borrowers, an alternative explanation is the existence of synergies between different types of lenders. For instance, private lenders and banks might typically provide firms with different debt instruments such as term loans and credit lines ([Haque et al., 2025](#)), leaving firms in an overall better position to pursue market growth. This conjecture directly suggests an analogous exercise to [Equation \(4\)](#) where we estimate the effects of the *presence of banks on top of private lenders* on our product market outcomes. If synergies between both types of lenders position the firm to better expand, such a test should generate similar results to those in [Section 4.2](#).

We perform a similar matching procedure to the one in [Section 3.3.2](#). Again, for firms with loans recorded in PitchBook, we select the first loan of each deal class financed by both banks and private lenders. Next, we form a pool of potential controls that closed their first deal of the same class and at the same month, but financed only by private lenders, and select the closest match following our usual product market matching. This procedure produces 81 treated units matched to their controls that form a sample of 24,036 firm-month observations. Of note, the difference between this sample and that from [Section 3.3.2](#) relies almost entirely on the control group, that is now restricted to firms

financed solely by private lenders instead of banks.³¹ Finally, we estimate a specification analogous to Equation (4) where *BankDebt* indicates the presence of bank in the firm's portfolio of lenders, and the DID coefficient measures the associated differential effect on the dependent variables.

We report these results in Table 6. Panel A shows a negative, nonsignificant estimate on overall product entry rate. Notably, entry rates on new and old modules go in opposite directions, with a positive, highly statistically significant result for products launched in new modules. Panel B shows positive, but nonsignificant estimates for store entry rates across new and old counties. Therefore, while we find mostly null results in Table 6, we cannot reject that bank lending facilitates higher product portfolio expansion towards new product lines based on these results alone (Granja and Moreira, 2022).

Insert Table 6 here

A clear caveat in our results in Table 6 is sample selection. Specifically, the comparison between bank and PD-financed firms with PD only-financed firms might not reflect the choice to pursue dual financing by treated firms, but the lack of access to bank financing by the firms in the control group. Potentially, growth-oriented, safer firms are better able to secure bank financing while control firms' lack access to traditional bank financing reflect their risky and stale nature. In such case, our estimates in Table 6 rely on comparisons between firms of distinct quality, an issue that our approach in Section 3.3.2 circumvents by design.

If our findings in this section primarily reflect access to bank financing, the effects should be attenuated for control firms with characteristics associated with such access. We test this by estimating heterogeneous effects using the proxies for bank financing access introduced in Section 5.2, namely firm beta and size. Specifically, we expect that if the results are driven by sample selection based on control firms' access to banks rather than synergies between private lenders and banks in financing product market strategies, any positive and significant estimates should be weaker or muted for large, low-beta control firms.

³¹The two additional cohorts in this exercise are due to bank and PD-financed firms for which we could find a PD-only financed control, but not a bank-only financed control in Section 3.3.2.

We report results in [Table 7](#). On both panels, we find mostly negative coefficients of the interaction terms. Notably, the positive estimates for product entry rates in new modules of [Table 6](#) are largely attenuated when control firms are larger and less risky. These results provide evidence those first results were mostly driven by sample selection: when focusing on cohorts for which the control firms are more likely to have access to bank financing, we find a significantly lower effect of the presence of banks on product expansion. The exception to this pattern is column (6) of Panel B, that suggests that firms that close dual-financed debt deals tend to increase presence in counties where they already operate even when compared to a large, PD-only financed control. While this can be evidence that dual financing still generates synergies that facilitate growth in safer, better-known markets, our analogous estimate using our firm beta measure is negative and significant. Therefore, the evidence is overall mixed concerning expansion in localities where firms already operate.

Insert [Table 7](#) here

6.2 Deal-level matching - Single deal

In the results described in [Section 4.2](#), our matching method considers the combination of a firm and its first loan of each deal class (debt or private equity) as a treated unit. Therefore, if a firm takes one pure-debt loan and another involving private equity where both have private debt and banks as financier, the firm can enter two cohorts as the treated unit. We follow this procedure to better utilize the richness of the PitchBook data and to ensure a sizable sample in our strict selection of counterfactuals. In addition, if the first deal tends to be more consequential in alleviating financing constraints relative to subsequent ones, this matching strategy would work against finding the results in [Table 3](#). On the other hand, patterns in the timing of loans could make these results heavily reliant on second deals if they are more closely linked to product market strategies. To ensure this is not the case, we repeat the procedure in [Section 3.3.2](#) restricting the sample to only the first loan ever recorded by each firm in the data.

For the sample of first loan deals of each firm, we take those that involve both private creditors and banks and classify them as the treated units. Next, we match them to first deals of the same class and at the same month following the description in [Section 3.3](#). As a result, cohorts here are defined at the treated firm level, since we consider single deal by firm. Naturally, this produces a

much smaller sample with 36 treated firms matched to their respective counterfactuals, out of which 25 loans are direct debt facilities whereas 11 have the participation of PE firms.³² The final sample consists of 10,199 firm-month observations of the matched pairs.

We report results from the estimation of Equation (4) on the restricted sample in Table 8. The estimates are largely similar to those in Table 3. Overall, initial deals with both banks and private creditors are associated with a 8.25 percentage point increase in post-deal sales entry from new products and a 6.78 percentage point increase from new stores. Once again, the effect is driven by new products across both existing and new product lines, as well as by availability in new stores located in previously unserved counties.

Insert Table 8 here

Our results in this test ensure that our baseline estimates reported in Section 4.2 are not driven by our treatment of deal classes in Section 3.3.2. In particular, the similar results in both approaches provide indirect evidence that pure debt and loans intermediated by private equity companies can compound in stirring market strategies and product development.

6.3 Financing status and LBO Matching

In our main specification, the matching procedure is based solely on deal class (debt vs. private equity-intermediated). However, within the debt category, some standard debt deals are taken by PE-backed firms, while others involve non-PE-backed firms. In the original setting, a treated PE-backed firm could therefore be matched with a control firm that is not PE-sponsored, making it difficult to disentangle whether our results are driven by private equity backing or by private debt becoming a new lender to the firm.

One potential concern is that firms obtaining private debt are more likely to be PE-backed, and the PE sponsor could use this capital productively to expand the firm's product lines. To address this, we add an additional layer to our matching procedure, pairing treated and control firms based on both financing status (PE-backed vs. non-PE-backed) and deal class (pure debt vs. PE-related deals).

³²See Figure IA.3 for the distribution of these loans over the sample years.

The stricter matching criteria reduce the sample size (report number of matches). [Table 9](#) reports the results. Consistent with our main findings, the presence of private debt in the lender panel is associated with higher sales entry rates from both new products and new stores. Panel A (column 2) shows that the increase in sales is driven by completely new modules, while Panel B (column 2) shows that sales growth comes from previously unserved counties. Overall, these results reinforce the positive role of private debt independent of PE backing.

Insert [Table 9](#) here

While this financing-status matching controls for PE involvement broadly, private equity deals are heterogeneous, and LBOs are known to generate particularly strong sales, profits, and product market expansion ([Boucly et al., 2011](#); [Fracassi et al., 2022](#)). If private debt is disproportionately present in LBOs, our results in [Section 4.2](#) could reflect LBO-driven effects rather than the presence of private creditors. To address this concern, we implement also an LBO-specific matching procedure.

We restrict our sample of deals to LBOs only. Although we allow multiple deals by firm when constructing cohorts, most firms go through only one LBO deal within our sample period. For each target of a LBO financed by both banks and private debt, we form a pool of controls that were also targets of LBOs at the same month, but financed solely by banks. From the pool of potential controls, we select the closest to the treated firm following our standard matching algorithm. This approach results in a severely restricted sample of 17 cohorts of treated-counterfactual units, covering 3,559 firm-month observations.

We report the estimation of [Equation \(4\)](#) on this restricted sample in [Table 10](#). The estimates indicate a significant increase in the sales entry rate from both new products (Panel A) and new stores (Panel B) following LBOs involving private creditors. Panel A shows that this effect is entirely driven by products launched in modules where the firm was already operating, as column (2) presents a non-significant—though positive and sizable—estimate for new modules. In contrast, for store entry (Panel B), the effect continues to be driven by entry into stores in new counties, as shown in column (2).

Insert [Table 10](#) here

The results in this robustness test provide evidence on the role of private creditors in consumer product development. Either by selection or post-deal influence, private debt-backed deals, in addition to bank financing, are associated with more product and store entry-driven sales even when comparing LBOs closed at the same month. The effects are concentrated in old product lines, which could potentially imply that private debt does not provide additional incentives for expansion toward new product lines. However, these results could simply reflect the limited statistical power of the restricted sample in this exercise.

7 Concluding Remarks

The private credit market continues to expand rapidly and is projected to reach \$2.64 trillion by 2029, drawing increasing attention from regulators concerned about market opacity and potential systemic risks. In this paper, we provide evidence of how the private lending penetration on the consumer goods sector finances product market expansion strategies of borrowers. Combining granular data at the product level with loan-level information, our analysis shows that companies financed through private debt deals innovate more relative to comparable firms financed solely by banks. This innovation comes both from expanding existing product lines and introducing new ones. Moreover, these firms significantly increase their geographic market reach, with new sales largely originating in previously unserved counties. Together, these findings suggest that private debt provide strategic financing to firms that pursue a dual growth strategy, simultaneously enhancing product offerings and expanding into new geographic markets.

While both PD and bank-only financing lead to higher revenues, PD is uniquely associated with product portfolio and geographic expansion. Our saturated empirical approach, which controls for confounding factors such as access to bank financing and the presence of private equity intermediaries, suggests that private lenders may play a meaningful role in firms' product market strategies. We identify managerial attention and industry expertise as potential channels, suggesting that private credit provides more than just capital. Instead, private debt providers actively contribute to firm growth by leveraging their sector knowledge to guide strategic decisions, facilitate market entry, and help firms navigate competitive dynamics. At the same time, more hands-on involvement and closer monitoring

allow them to support the implementation of operational improvements and the commercialization of new products. Taken together, these non-financial contributions highlight how private credit can act as a strategic partner rather than a passive financier.

As regulators weigh the risks of opacity in private credit markets and consider enhancing investor protection, our findings offer new insights for the policy debate. These results document that private credit can support both product market and geographic expansion, contributing to broader economic dynamism, despite valid concerns around transparency and liquidity risk. These benefits should be carefully weighed in the development of a balanced regulatory framework, one that preserves the positive economic contributions of private debt while effectively addressing its potential vulnerabilities

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Table 1. Summary Statistics. This table reports descriptive statistics of the our full sample of our full matched sample described in Section 3.3.1. Observations are at the firm-month level and span from January 2006 to December 2023. Panel A reports the number of observations, mean, standard deviations and quartiles. *Total sales* are firm’s monthly total sales in thousands of dollars. *Number of products* is the count of unique different products manufactured by a firm. *Number of modules* is the count of unique product categories that a firm’s product portfolio covers. *Number of stores* is the count of stores with products from a firm, and *Number of counties* is the count of US counties with products from a firm. *Product Entry Rate (All Modules)* is the ratio of revenues generated by new products to firm’s total sales. *Product Entry Rate (New Modules)* is the ratio of revenues generated by new products in new modules to firm’s total sales. *Product Entry Rate (Old Modules)* is the ratio of revenues generated by new products in old modules to firm’s total sales. We consider a product new during the 6 months with recorded sales in the dataset. We consider a firm-module new within 12 months of its first appearance in the dataset. *Store Entry Rate (All Counties)* is the ratio of revenues generated in stores where the firm recently entered to its total sales. *Store Entry Rate (New Counties)* is the ratio of revenues generated in stores and counties where the firm recently entered to its total sales. *Store Entry Rate (Old Counties)* is the ratio of revenues in stores where the firm recently entered in counties where it previously operated to its total sales. We consider store entry by a firm recent during the first 6 months with recorded sales by a firm in a store. We consider county entry by a firm recent during the first 12 months with recorded sales of a firm in a county. Entry rates are expressed in percentage points. *Active Lender* is a indicator of a firm having an outstanding loan is a given month. *Active Bank* and *Active Private* is an indicator of having an outstanding loan with a bank and private lender, respectively. Panel B reports descriptive statistics of variables used in the matching procedure in the month prior to treated firms’ first deal. Treated firms are those with loans reported in the data between 2007 and 2022. Control firms are those without any loan recorded during the sample period. Each treated firm is matched to a single counterfactual at the month prior to the first loan of the treated firm. A treated-control group is defined as a *cohort* and the sample is a stack of cohorts. The last column of panel B reports the *p*-value of a *t*-test between the means of treated and control firms. See Section 3.3.1 for details of the matching procedure, and Section 3.2 for details on variable construction.

Panel A. Full Matched Sample

Statistic	N	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
Total Sales (in thousands)	288,234	1,402.28	6,650.49	4.65	57.15	468.22
Sales Growth	265,519	3.46	94.22	-25.48	2.25	31.66
Number of Products	288,234	70.51	273.60	4	13	42
Number of Modules	288,234	6.07	11.78	1	3	6
Number of Stores	288,234	3,545.95	6,547.61	73	564	3,788
Number of Counties	288,234	524.00	667.93	26	176	829
Product Entry Rate (All Modules)	288,234	8.46	21.85	0.00	0.00	2.98
Product Entry Rate (New Modules)	288,234	1.31	9.05	0.00	0.00	0.00
Product Entry Rate (Old Modules)	288,234	7.15	19.90	0.00	0.00	1.94
Store Entry Rate (All States)	288,234	12.12	24.11	0.51	1.94	8.87
Store Entry Rate (New States)	288,234	6.95	20.47	0.00	0.08	1.52
Store Entry Rate (Old States)	288,234	5.17	11.89	0.16	1.18	4.01
Active Lender	288,234	0.17	0.38	0	0	0
Active Bank	288,234	0.13	0.34	0	0	0
Active Private	288,234	0.06	0.24	0	0	0

Panel B. Sample Balance

Statistic	Treated Firms			Control Firms			Mean Diff. <i>p</i> -value
	N	Mean	St. Dev.	N	Mean	St. Dev.	
Total Sales (in thousands)	999	3,584.88	35,373.84	999	2,996.35	25,853.31	0.67
Sales Growth (%)	999	0.81	148.18	999	-0.16	146.65	0.88
Number of Products	999	85.64	374.97	999	74.13	278.81	0.44
Number of Modules	999	6.59	17.16	999	6.32	14.71	0.71
Number of Stores	999	3,516.70	6,922.48	999	3,512.14	6,921.03	0.99
Number of Counties	999	509.64	664.98	999	506.11	662.34	0.91

Table 2. Active Loans: Banks versus Private lenders. This table reports the coefficients from the estimation of Equation (1) and Equation (2). The dependent variables are the log of total sales and sales-weighted entry rate. *Total sales* is the monthly total revenues generated by a firm’s products. In columns (1)–(2), the reported estimate corresponds to $100(e^{\beta} - 1)$ where β is the coefficient of Equation (1) or Equation (2) with total sales in log-level, and the standard errors are adjusted accordingly using the Delta method. *Product Entry Rate* is the ratio of sales generated by new products to a firm’s total sales. We consider a product new during the 6 months with recorded sales in the dataset. *Store Entry Rate* is the ratio of revenues generated in stores where the firm recently entered to its total sales. We consider store entry by a firm recent during the first 6 months with recorded sales by a firm in a store. Entry rates are expressed in percentage points. *Active Lender* is an indicator of a firm having an outstanding loan in a given month. *Active Bank* and *Active Private* are indicators of having an outstanding loan with a bank and private lender, respectively. The sample consists of firm-month-level observations of treated firms matched to counterfactual controls. Treated firms are those with loans reported in the data between 2007 and 2022. Control firms are those without any loan recorded during the sample period. Each treated firm is matched to a single counterfactual based on total sales, sales growth and number of products, modules, stores, and counties at the month prior to the first loan of the treated firm. A treated-control group is defined as a *cohort* and the sample is a stack of cohorts. See Section 3.3.1 for details of the matching procedure, and Section 3.2 for details on variable construction. *t*-statistics are reported in parentheses. Standard errors are two-way clustered by firm and month-year. †, *, **, and *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% levels, respectively.

	<i>Dependent variable:</i>					
	Total Sales		Product Entry Rate		Store Entry Rate	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>ActiveLender</i>	63.36 (6.42)***		−1.28 (−3.03)**		−2.05 (−4.37)***	
<i>ActivePrivate</i>		37.50 (2.64)**		5.19 (7.55)***		1.56 (2.27)*
<i>ActiveBank</i>		41.19 (4.01)***		−4.15 (−8.69)***		−2.84 (−5.30)***
Firm-Cohort FE	Y	Y	Y	Y	Y	Y
Month-Year-Cohort	Y	Y	Y	Y	Y	Y
Observations	288,234	288,234	288,234	288,234	288,234	288,234
Adjusted R ²	0.82	0.82	0.35	0.35	0.43	0.43

Note: † p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Table 3. Presence of Private Lenders This table reports the coefficients from the estimation of Equation (4). The dependent variables are sales-weighted entry rates. *Product Entry Rate (All Modules)* is the ratio of revenues generated by new products to firm’s total sales. *Product Entry Rate (New Modules)* is the ratio of revenues generated by new products in new modules to firm’s total sales. *Product Entry Rate (Old Modules)* is the ratio of revenues generated by new products in old modules to firm’s total sales. We consider a product new during the 6 months with recorded sales in the dataset. We consider a firm-module new within 12 months of its first appearance in the dataset. *Store Entry Rate (All Counties)* is the ratio of revenues generated in stores where the firm recently entered to its total sales. *Store Entry Rate (New Counties)* is the ratio of revenues generated in stores and counties where the firm recently entered to its total sales. *Store Entry Rate (Old Counties)* is the ratio of revenues in stores where the firm recently entered in counties where it previously operated to its total sales. We consider store entry by a firm recent during the first 6 months with recorded sales by a firm in a store. We consider county entry by a firm recent during the first 12 months with recorded sales of a firm in a county. Entry rates are expressed in percentage points. *PrivateDebt* is an indicator of a firm having at least one private lender in its loan. *Post* is an indicator of periods after the the treated firm’s loan. The sample consists of firm-month-level observations of treated firms matched to counterfactual controls. Treated units are firm-loan classes (debt of private equity) that have both private lenders and banks in the mix of creditors. Control firms are those with only banks as creditors. Each treated firm-loan class is matched to a single counterfactual that took its first loan of the same class in the same month of the treated firm’s first loan of that class. The match is based on total sales, sales growth and number of products, modules, stores, and counties at the month prior to the first loan of the treated firm. A treated-control group is defined as a *cohort* and the sample is a stack of cohorts. See Section 3.3.2 for details of the matching procedure, and Section 3.2 for details on variable construction. *t*-statistics are reported in parentheses. Standard errors are two-way clustered by firm and month-year. †, *, **, and *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% levels, respectively.

Panel A. Product Entry

	<i>Product Entry Rate</i>		
	All Modules	New Modules	Old Modules
	(1)	(2)	(3)
<i>PrivateDebt</i> × <i>Post</i>	5.74 (3.53)***	1.52 (2.87)**	4.22 (2.83)**
Firm-Cohort FE	✓	✓	✓
Month-Year-Cohort	✓	✓	✓
Observations	22,041	22,041	22,041
Adjusted R ²	0.35	0.10	0.37

Panel B. Store Entry

	<i>Store Entry Rate</i>		
	All Counties	New Counties	Old Counties
	(1)	(2)	(3)
<i>PrivateDebt</i> × <i>Post</i>	4.95 (2.26)*	5.40 (2.87)**	−0.46 (−0.44)
Firm-Cohort FE	✓	✓	✓
Month-Year-Cohort	✓	✓	✓
Observations	22,041	22,041	22,041
Adjusted R ²	0.32	0.28	0.26

Note: † p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Table 4. Presence of Private Lenders: Heterogeneity by Lender Characteristics. This table reports the coefficients from the estimation of a triple differences specification where we add a lender-level cross-sectional variable to form a triple interaction term in Equation (4). The dependent variables are sales-weighted entry rates. *Product Entry Rate (All Modules)* is the ratio of revenues generated by new products to firm’s total sales. *Product Entry Rate (New Modules)* is the ratio of revenues generated by new products in new modules to firm’s total sales. *Product Entry Rate (Old Modules)* is the ratio of revenues generated by new products in old modules to firm’s total sales. We consider a product new during the 6 months with recorded sales in the dataset. We consider a firm-module new within 12 months of its first appearance in the dataset. *Store Entry Rate (All Counties)* is the ratio of revenues generated in stores where the firm recently entered to its total sales. *Store Entry Rate (New Counties)* is the ratio of revenues generated in stores and counties where the firm recently entered to its total sales. *Store Entry Rate (Old Counties)* is the ratio of revenues in stores where the firm recently entered in counties where it previously operated to its total sales. We consider store entry by a firm recent during the first 6 months with recorded sales by a firm in a store. We consider county entry by a firm recent during the first 12 months with recorded sales of a firm in a county. Entry rates are expressed in percentage points. *PrivateDebt* is an indicator of a firm having at least one private lender in its loan. *Post* is an indicator of periods after the the treated firm’s loan. The sample consists of firm-month-level observations of treated firms matched to counterfactual controls. Treated units are firm-loan classes (debt of private equity) that have both private lenders and banks in the mix of creditors. Control firms are those with only banks as creditors. Each treated firm-loan class is matched to a single counterfactual that took its first loan of the same class in the same month of the treated firm’s first loan of that class. The match is based on total sales, sales growth and number of products, modules, stores, and counties at the month prior to the first loan of the treated firm. *Fundsize* is the logarithm of the cumulative average size of the funds involved in the matched deal. *Specialized* is an indicator variable that equals 1 if the share of private debt lenders participating in a given deal who are specialized in the industry of the treated firm is above the sample mean, and 0 otherwise. We consider a fund specialized in the industry where it complete the largest number of deals, provided that the fund completed at least four deals up to a given month. See Section 5 for details on the construction of fund-level cross-sectional variables. A treated-control group is defined as a *cohort* and the sample is a stack of cohorts. See Section 3.3.2 for details of the matching procedure, and Section 3.2 for details on variable construction. *t*-statistics are reported in parentheses. Standard errors are two-way clustered by firm and month-year. †, *, **, and *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% levels, respectively.

Panel A. Product Entry

	<i>Product Entry Rate</i>					
	All Modules		New Modules		Old Modules	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>PrivateDebt</i> × <i>Post</i>	44.50 (2.95)**	2.40 (1.19)	9.57 (2.13)*	0.27 0.(61)	34.93 (2.44)*	2.13 (1.11)
<i>PrivateDebt</i> × <i>Post</i> × <i>FundSize</i>	− 5.89 (− 2.74)**		− 1.15 (− 2.10)*		− 4.74 (− 2.32)*	
<i>PrivateDebt</i> × <i>Post</i> × <i>Specialized</i>	9.76 (2.82)**		2.73 (2.55)*		7.03 (2.10)*	
Firm-Cohort FE	Y	Y	Y	Y	Y	Y
Month-Year-Cohort	Y	Y	Y	Y	Y	Y
Observations	11,141	15,797	11,141	15,797	11,141	15,797
Adjusted R ²	0.34	0.32	0.17	0.12	0.38	0.34

Note:

† p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Presence of Private Lenders: Heterogeneity (Continued)

Panel B. Store Entry

	<i>Store Entry Rate</i>					
	All Counties		New Counties		Old Counties	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>PrivateDebt</i> × <i>Post</i>	47.04 (4.95) ^{***}	-2.13 (-0.88)	40.56 (3.10) ^{**}	-0.59 (-0.25)	-2.39 (0.68)	6.47 (-1.42)
<i>PrivateDebt</i> × <i>Post</i> × <i>FundSize</i>	-6.08 (- 4.29) ^{***}		-5.14 (-2.79) ^{**}		-0.94 (-0.70)	
<i>PrivateDebt</i> × <i>Post</i> × <i>Specialized</i>	11.51 (2.45) [*]		11.17 (2.94) ^{**}		0.35 (0.16)	
Firm-Cohort FE	Y	Y	Y	Y	Y	Y
Month-Year-Cohort	Y	Y	Y	Y	Y	Y
Observations	11,141	15,797	11,141	15,797	11,141	15,797
Adjusted R ²	0.37	0.31	0.31	0.27	0.34	0.30

Note:

[†] p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Table 5. Presence of Private Lenders: Heterogeneity by Borrower Risk and Size. This table reports the coefficients from the estimation of Equation (4). The dependent variables are sales-weighted entry rates. *Product Entry Rate (All Modules)* is the ratio of revenues generated by new products to firm’s total sales. *Product Entry Rate (New Modules)* is the ratio of revenues generated by new products in new modules to firm’s total sales. *Product Entry Rate (Old Modules)* is the ratio of revenues generated by new products in old modules to firm’s total sales. We consider a product new during the 6 months with recorded sales in the dataset. We consider a firm-module new within 12 months of its first appearance in the dataset. *Store Entry Rate (All Counties)* is the ratio of revenues generated in stores where the firm recently entered to its total sales. *Store Entry Rate (New Counties)* is the ratio of revenues generated in stores and counties where the firm recently entered to its total sales. *Store Entry Rate (Old Counties)* is the ratio of revenues in stores where the firm recently entered in counties where it previously operated to its total sales. We consider store entry by a firm recent during the first 6 months with recorded sales by a firm in a store. We consider county entry by a firm recent during the first 12 months with recorded sales of a firm in a county. Entry rates are expressed in percentage points. *PrivateDebt* is an indicator of a firm having at least one private lender in its loan. *Post* is an indicator of periods after the the treated firm’s loan. The sample consists of firm-month-level observations of treated firms matched to counterfactual controls. Treated units are firm-loan classes (debt of private equity) that have both private lenders and banks in the mix of creditors. Control firms are those with only banks as creditors. Each treated firm-loan class is matched to a single counterfactual that took its first loan of the same class in the same month of the treated firm’s first loan of that class. The match is based on total sales, sales growth and number of products, modules, stores, and counties at the month prior to the first loan of the treated firm. *LowBeta* is an indicator variable that equals 1 when the treated firm has a firm beta below the sample average, where beta is the sensitivity of the firm’s revenues to aggregate revenue in the firm’s industry. *Large* is an indicator variable that equals 1 if the treated firm’s total revenue is above the sample average. A treated-control group is defined as a *cohort* and the sample is a stack of cohorts. See Section 3.3.2 for details of the matching procedure, and Sections 3.2 and 5.2 for details on variable construction. *t*-statistics are reported in parentheses. Standard errors are two-way clustered by firm and month-year. †, *, **, and *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% levels, respectively.

Panel A. Product Entry

	<i>Product Entry Rate</i>					
	All Modules		New Modules		Old Modules	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>PrivateDebt</i> × <i>Post</i>	5.71 (2.19)*	5.07 (2.75)**	1.58 (1.66)†	1.32 (2.07)*	4.12 (1.72)†	3.75 (2.22)*
<i>PrivateDebt</i> × <i>Post</i> × <i>LowBeta</i>	−0.99 (−0.31)		−0.13 (−0.11)		−0.86 (−0.30)	
<i>PrivateDebt</i> × <i>Post</i> × <i>Large</i>	0.62 (0.14)		0.93 (0.69)		−0.31 (−0.09)	
Firm-Cohort FE	Y	Y	Y	Y	Y	Y
Month-Year-Cohort	Y	Y	Y	Y	Y	Y
Observations	20,611	20,611	20,611	20,611	20,611	20,611
Adjusted R ²	0.36	0.36	0.12	0.12	0.37	0.37

Note: † p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Presence of Private Lenders: Heterogeneity by Risk and Size. (Continued)

Panel B. Store Entry

	<i>Store Entry Rate</i>					
	All Counties		New Counties		Old Counties	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>PrivateDebt</i> × <i>Post</i>	3.40 (1.01)	5.00 (1.74) [†]	3.25 (1.03)	5.24 (2.12)*	0.15 (0.11)	-0.24 (-0.19)
<i>PrivateDebt</i> × <i>Post</i> × <i>LowBeta</i>	2.29 (0.57)		3.20 (0.91)		-0.91 (-0.47)	
<i>PrivateDebt</i> × <i>Post</i> × <i>Large</i>		-2.02 (-0.60)		-1.66 (-0.51)		-0.36 (-0.27)
Firm-Cohort FE	Y	Y	Y	Y	Y	Y
Month-Year-Cohort	Y	Y	Y	Y	Y	Y
Observations	20,611	20,611	20,611	20,611	20,611	20,611
Adjusted R ²	0.31	0.31	0.26	0.26	0.26	0.26

Note:

[†] p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Table 6. Presence of Banks This table reports the coefficients from the estimation of Equation (4). The dependent variables are sales-weighted entry rates. *Product Entry Rate (All Modules)* is the ratio of revenues generated by new products to firm’s total sales. *Product Entry Rate (New Modules)* is the ratio of revenues generated by new products in new modules to firm’s total sales. *Product Entry Rate (Old Modules)* is the ratio of revenues generated by new products in old modules to firm’s total sales. We consider a product new during the 6 months with recorded sales in the dataset. We consider a firm-module new within 12 months of its first appearance in the dataset. *Store Entry Rate (All Counties)* is the ratio of revenues generated in stores where the firm recently entered to its total sales. *Store Entry Rate (New Counties)* is the ratio of revenues generated in stores and counties where the firm recently entered to its total sales. *Store Entry Rate (Old Counties)* is the ratio of revenues in stores where the firm recently entered in counties where it previously operated to its total sales. We consider store entry by a firm recent during the first 6 months with recorded sales by a firm in a store. We consider county entry by a firm recent during the first 12 months with recorded sales of a firm in a county. Entry rates are expressed in percentage points. *BankDebt* is an indicator of a firm having at least one bank in its loan. *Post* is an indicator of periods after the treated firm’s loan. The sample consists of firm-month-level observations of treated firms matched to counterfactual controls. Treated units are firm-loan classes (debt of private equity) that have both private lenders and banks in the mix of creditors. Control firms are those with only private lenders as creditors. Each treated firm-loan class is matched to a single counterfactual that took its first loan of the same class in the same month of the treated firm’s first loan of that class. The match is based on total sales, sales growth and number of products, modules, stores, and counties at the month prior to the first loan of the treated firm. A treated-control group is defined as a *cohort* and the sample is a stack of cohorts. See Section 3.3.2 for details of the matching procedure, and Section 3.2 for details on variable construction. *t*-statistics are reported in parentheses. Standard errors are two-way clustered by firm and month-year. †, *, **, and *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% levels, respectively.

Panel A. Product Entry

	<i>Product Entry Rate</i>		
	All Modules	New Modules	Old Modules
	(1)	(2)	(3)
<i>BankDebt</i> × <i>Post</i>	−0.86 (−0.46)	1.99 (3.49)***	−2.85 (−1.70)†
Firm-Cohort FE	✓	✓	✓
Month-Year-Cohort	✓	✓	✓
Observations	24,036	24,036	24,036
Adjusted R ²	0.27	0.10	0.25

Panel B. Store Entry

	<i>Store Entry Rate</i>		
	All Counties	New Counties	Old Counties
	(1)	(2)	(3)
<i>BankDebt</i> × <i>Post</i>	3.52 (1.78)†	2.57 (1.50)	0.95 (1.00)
Firm-Cohort FE	✓	✓	✓
Month-Year-Cohort	✓	✓	✓
Observations	24,036	24,036	24,036
Adjusted R ²	0.33	0.26	0.24

Note: † p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Table 7. Presence of Banks: Heterogeneity by Risk and Size This table reports the coefficients from the estimation of Equation (4). The dependent variables are sales-weighted entry rates. *Product Entry Rate (All Modules)* is the ratio of revenues generated by new products to firm’s total sales. *Product Entry Rate (New Modules)* is the ratio of revenues generated by new products in new modules to firm’s total sales. *Product Entry Rate (Old Modules)* is the ratio of revenues generated by new products in old modules to firm’s total sales. We consider a product new during the 6 months with recorded sales in the dataset. We consider a firm-module new within 12 months of its first appearance in the dataset. *Store Entry Rate (All Counties)* is the ratio of revenues generated in stores where the firm recently entered to its total sales. *Store Entry Rate (New Counties)* is the ratio of revenues generated in stores and counties where the firm recently entered to its total sales. *Store Entry Rate (Old Counties)* is the ratio of revenues in stores where the firm recently entered in counties where it previously operated to its total sales. We consider store entry by a firm recent during the first 6 months with recorded sales by a firm in a store. We consider county entry by a firm recent during the first 12 months with recorded sales of a firm in a county. Entry rates are expressed in percentage points. *BankDebt* is an indicator of a firm having at least one bank lender in its loan. *Post* is an indicator of periods after the the treated firm’s loan. The sample consists of firm-month-level observations of treated firms matched to counterfactual controls. Treated units are firm-loan classes (debt of private equity) that have both private lenders and banks in the mix of creditors. Control firms are those with only private lenders as creditors. Each treated firm-loan class is matched to a single counterfactual that took its first loan of the same class in the same month of the treated firm’s first loan of that class. The match is based on total sales, sales growth and number of products, modules, stores, and counties at the month prior to the first loan of the treated firm. *LowBeta* is an indicator variable that equals 1 when the control firm has a firm beta below the sample average, where beta is the sensitivity of the firm’s revenues to aggregate revenue in the firm’s industry. *Large* is an indicator variable that equals 1 if the control firm’s total revenue is above the sample average. A treated-control group is defined as a *cohort* and the sample is a stack of cohorts. See Section 3.3.2 for details of the matching procedure, and Sections 3.2 and 5.2 for details on variable construction. *t*-statistics are reported in parentheses. Standard errors are two-way clustered by firm and month-year. †, *, **, and *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% levels, respectively.

Panel A. Product Entry

	<i>Product Entry Rate</i>					
	All Modules		New Modules		Old Modules	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>BankDebt</i> × <i>Post</i>	2.33 (1.06)	−0.74 (−0.34)	3.65 (4.69)***	2.29 (3.33)**	−1.32 (−0.60)	−3.03 (−1.54)
<i>BankDebt</i> × <i>Post</i> × <i>LowBeta</i>	−6.32 (−1.75)†		−3.28 (−3.08)**		−3.03 (−0.90)	
<i>BankDebt</i> × <i>Post</i> × <i>Large</i>		−0.68 (−0.23)		−1.74 (−2.02)*		1.06 (0.40)
Firm-Cohort FE	Y	Y	Y	Y	Y	Y
Month-Year-Cohort	Y	Y	Y	Y	Y	Y
Observations	24,036	24,036	24,036	24,036	24,036	24,036
Adjusted R ²	0.27	0.27	0.10	0.10	0.25	0.25

Note: † p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Presence of Banks: Heterogeneity by Risk and Size (Continued)

Panel B. Store Entry

	<i>Store Entry Rate</i>					
	All Counties		New Counties		Old Counties	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>BankDebt</i> × <i>Post</i>	7.36 (2.51)*	3.57 (1.54)	4.17 (1.39)	3.62 (1.79) [†]	3.19 (2.40)*	-0.06 (-0.06)
<i>BankDebt</i> × <i>Post</i> × <i>LowBeta</i>	-7.61 (-2.02)*		-3.17 (-0.92)		-4.44 (-2.37)*	
<i>BankDebt</i> × <i>Post</i> × <i>Large</i>		-0.29 (-0.08)		-6.15 (-2.23)*		5.86 (2.41)*
Firm-Cohort FE	✓	✓	✓	✓	✓	✓
Month-Year-Cohort	✓	✓	✓	✓	✓	✓
Observations	24,036	24,036	24,036	24,036	24,036	24,036
Adjusted R ²	0.33	0.33	0.26	0.26	0.24	0.24

Note:

[†] p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Table 8. Presence of Private Lenders: Single deals This table reports the coefficients from the estimation of Equation (4). The dependent variables are sales-weighted entry rates. *Product Entry Rate (All Modules)* is the ratio of revenues generated by new products to firm’s total sales. *Product Entry Rate (New Modules)* is the ratio of revenues generated by new products in new modules to firm’s total sales. *Product Entry Rate (Old Modules)* is the ratio of revenues generated by new products in old modules to firm’s total sales. We consider a product new during the 6 months with recorded sales in the dataset. We consider a firm-module new within 12 months of its first appearance in the dataset. *Store Entry Rate (All Counties)* is the ratio of revenues generated in stores where the firm recently entered to its total sales. *Store Entry Rate (New Counties)* is the ratio of revenues generated in stores and counties where the firm recently entered to its total sales. *Store Entry Rate (Old Counties)* is the ratio of revenues in stores where the firm recently entered in counties where it previously operated to its total sales. We consider store entry by a firm recent during the first 6 months with recorded sales by a firm in a store. We consider county entry by a firm recent during the first 12 months with recorded sales of a firm in a county. Entry rates are expressed in percentage points. *PrivateDebt* is an indicator of a firm having at least one private lender in its loan. *Post* is an indicator of periods after the the treated firm’s loan. The sample consists of firm-month-level observations of treated firms matched to counterfactual controls. Treated firms have both private lenders and banks in the mix of creditors of their first loan. Control firms are those with only banks as creditors. Each treated firm is matched to a single counterfactual that took its first loan of the same class (debt of private equity) in the same month of the treated firm’s first loan. The match is based on total sales, sales growth and number of products, modules, stores, and counties at the month prior to the first loan of the treated firm. A treated-control group is defined as a *cohort* and the sample is a stack of cohorts. See Section 3.3.2 and Section 6.2 for details of the matching procedure, and Section 3.2 for details on variable construction. *t*-statistics are reported in parentheses. Standard errors are two-way clustered by firm and month-year. †, *, **, and *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% levels, respectively.

Panel A. Product Entry

	<i>Product Entry Rate</i>		
	All Modules	New Modules	Old Modules
	(1)	(2)	(3)
<i>PrivateDebt</i> × <i>Post</i>	8.25 (3.50)***	2.70 (2.89)**	5.55 (2.54)*
Firm-Cohort FE	✓	✓	✓
Month-Year-Cohort	✓	✓	✓
Observations	10,584	10,584	10,584
Adjusted R ²	0.21	0.11	0.25

Panel B. Store Entry

	<i>Store Entry Rate</i>		
	All Counties	New Counties	Old Counties
	(1)	(2)	(3)
<i>PrivateDebt</i> × <i>Post</i>	6.79 (2.55)*	7.41 (3.35)**	-0.62 (-0.36)
Firm-Cohort FE	✓	✓	✓
Month-Year-Cohort	✓	✓	✓
Observations	10,584	10,584	10,584
Adjusted R ²	0.30	0.29	0.26

Note: † p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Table 9. Presence of Private Lenders: Matching by Financing Status This table reports the coefficients from the estimation of Equation (4). The dependent variables are sales-weighted entry rates. *Product Entry Rate (All Modules)* is the ratio of revenues generated by new products to firm’s total sales. *Product Entry Rate (New Modules)* is the ratio of revenues generated by new products in new modules to firm’s total sales. *Product Entry Rate (Old Modules)* is the ratio of revenues generated by new products in old modules to firm’s total sales. We consider a product new during the 6 months with recorded sales in the dataset. We consider a firm-module new within 12 months of its first appearance in the dataset. *Store Entry Rate (All Counties)* is the ratio of revenues generated in stores where the firm recently entered to its total sales. *Store Entry Rate (New Counties)* is the ratio of revenues generated in stores and counties where the firm recently entered to its total sales. *Store Entry Rate (Old Counties)* is the ratio of revenues in stores where the firm recently entered in counties where it previously operated to its total sales. We consider store entry by a firm recent during the first 6 months with recorded sales by a firm in a store. We consider county entry by a firm recent during the first 12 months with recorded sales of a firm in a county. Entry rates are expressed in percentage points. *PrivateDebt* is an indicator of a firm having at least one private lender in its loan. *Post* is an indicator of periods after the the treated firm’s loan. The sample consists of firm-month-level observations of treated firms matched to counterfactual controls. Treated units are firm-loan classes (debt of private equity) that have both private lenders and banks in the mix of creditors. Control firms are those with only banks as creditors. Each treated firm-loan class is matched to a single counterfactual that took its first loan of the same class in the same month of the treated firm’s first loan of that class and with the same financing status. The match is based on total sales, sales growth and number of products, modules, stores, and counties at the month prior to the first loan of the treated firm. A treated-control group is defined as a *cohort* and the sample is a stack of cohorts. See Section 3.3.2 and Section 6.3 for details of the matching procedure, and Section 3.2 for details on variable construction. *t*-statistics are reported in parentheses. Standard errors are two-way clustered by firm and month-year. †, *, **, and *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% levels, respectively.

Panel A. Product Entry

	<i>Product Entry Rate</i>		
	All Modules	New Modules	Old Modules
	(1)	(2)	(3)
<i>PrivateDebt</i> × <i>Post</i>	5.08 (1.80) [†]	1.22 (2.74)**	3.86 (1.46)
Firm-Cohort FE	Y	Y	Y
Month-Year-Cohort	Y	Y	Y
Observations	8,495	8,495	8,495
Adjusted R ²	0.35	0.19	0.38

Panel B. Store Entry

	<i>Store Entry Rate</i>		
	All Counties	New Counties	Old Counties
	(1)	(2)	(3)
<i>PrivateDebt</i> × <i>Post</i>	7.97 (2.57)*	6.48 (2.09)*	1.50 (0.87)
Firm-Cohort FE	Y	Y	Y
Month-Year-Cohort	Y	Y	Y
Observations	8,495	8,495	8,495
Adjusted R ²	0.36	0.30	0.21

Note: † p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Table 10. Presence of Private Lenders: Leveraged Buyouts This table reports the coefficients from the estimation of Equation (4). The dependent variables are sales-weighted entry rates. *Product Entry Rate (All Modules)* is the ratio of revenues generated by new products to firm’s total sales. *Product Entry Rate (New Modules)* is the ratio of revenues generated by new products in new modules to firm’s total sales. *Product Entry Rate (Old Modules)* is the ratio of revenues generated by new products in old modules to firm’s total sales. We consider a product new during the 6 months with recorded sales in the dataset. We consider a firm-module new within 12 months of its first appearance in the dataset. *Store Entry Rate (All Counties)* is the ratio of revenues generated in stores where the firm recently entered to its total sales. *Store Entry Rate (New Counties)* is the ratio of revenues generated in stores and counties where the firm recently entered to its total sales. *Store Entry Rate (Old Counties)* is the ratio of revenues in stores where the firm recently entered in counties where it previously operated to its total sales. We consider store entry by a firm recent during the first 6 months with recorded sales by a firm in a store. We consider county entry by a firm recent during the first 12 months with recorded sales of a firm in a county. Entry rates are expressed in percentage points. *PrivateDebt* is an indicator of a firm having at least one private lender in its loan. *Post* is an indicator of periods after the the treated firm’s loan. The sample consists of firm-month-level observations of treated firms matched to counterfactual controls. In this sample, only LBO deals are considered. Treated units are firm-loan classes (debt of private equity) that have both private lenders and banks in the mix of creditors. Control firms are those with only banks as creditors. Each treated firm-loan class is matched to a single counterfactual that took its first loan of the same class in the same month of the treated firm’s first loan of that class. The match is based on total sales, sales growth and number of products, modules, stores, and counties at the month prior to the first loan of the treated firm. A treated-control group is defined as a *cohort* and the sample is a stack of cohorts. See Section 3.3.2 and Section 6.3 for details of the matching procedure, and Section 3.2 for details on variable construction. *t*-statistics are reported in parentheses. Standard errors are two-way clustered by firm and month-year. †, *, **, and *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% levels, respectively.

Panel A. Product Entry

	<i>Product Entry Rate</i>		
	All Modules	New Modules	Old Modules
	(1)	(2)	(3)
<i>PrivateDebt</i> × <i>Post</i>	12.85 (2.59)*	−0.09 (−0.15)	12.94 (2.69)*
Firm-Cohort FE	✓	✓	✓
Month-Year-Cohort	✓	✓	✓
Observations	3,582	3,582	3,582
Adjusted R ²	0.53	0.56	0.49

Panel B. Store Entry

	<i>Store Entry Rate</i>		
	All Counties	New Counties	Old Counties
	(1)	(2)	(3)
<i>PrivateDebt</i> × <i>Post</i>	11.37 (2.07)*	13.33 (2.58)*	−1.96 (−0.87)
Firm-Cohort FE	✓	✓	✓
Month-Year-Cohort	✓	✓	✓
Observations	3,582	3,582	3,582
Adjusted R ²	0.41	0.36	−0.02

Note: † p<0.1; * p<0.05; ** p<0.01; *** p<0.001

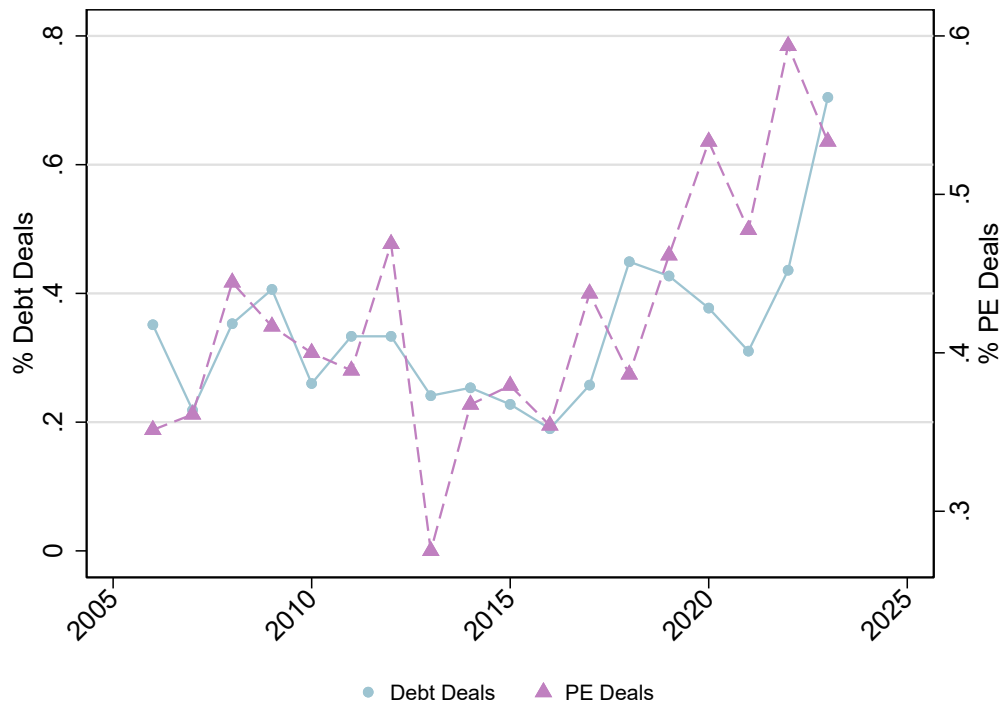


Figure 1. The figure presents the percentage of Private Equity and Pure Debt deals financed by at least one private debt provider over the period 2006–2023. PE deals include Buyout/LBO and PE Growth/Expansion deals, while Debt deals include Debt – General and Debt – Acquisition deals (as defined in PitchBook). The solid line represents debt deals, while the dashed line represents PE deals. Only deals involving companies included in the NielsenIQ dataset, i.e., manufacturers of consumer products are considered.

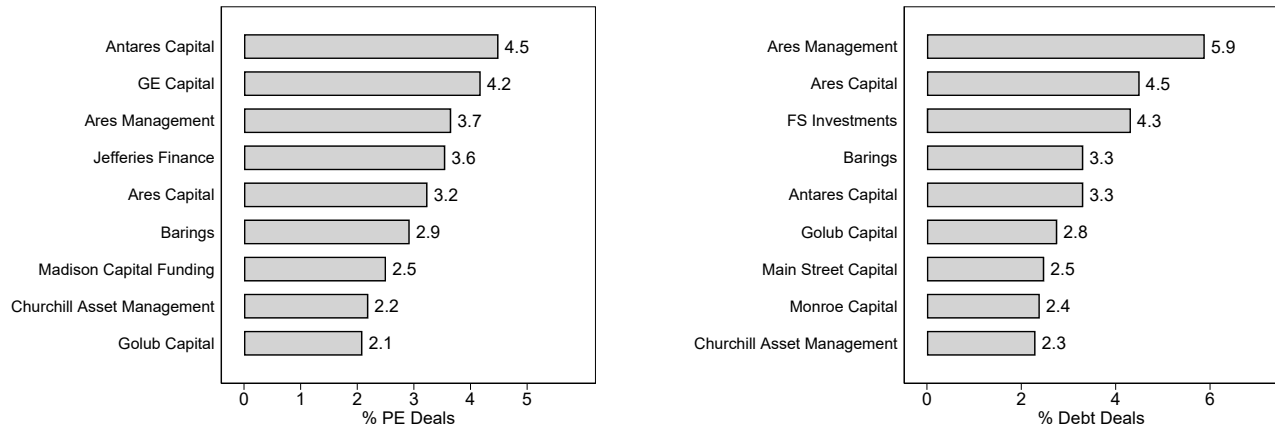
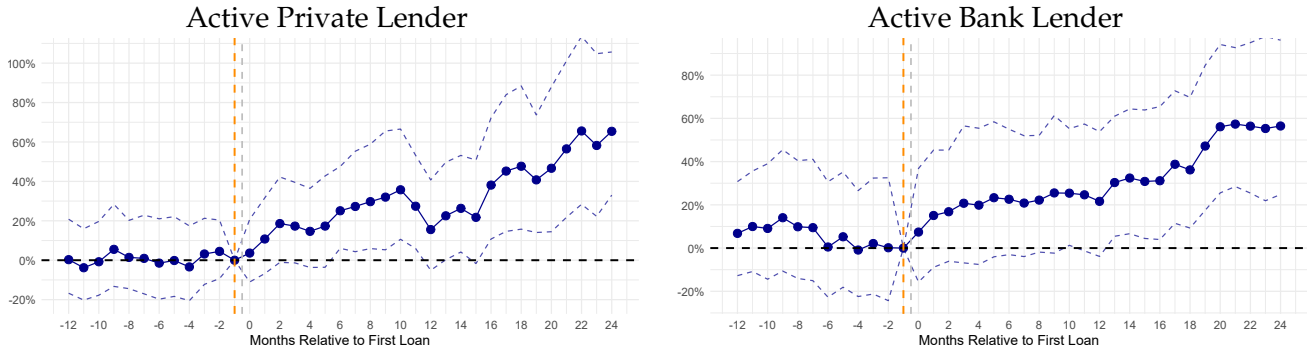
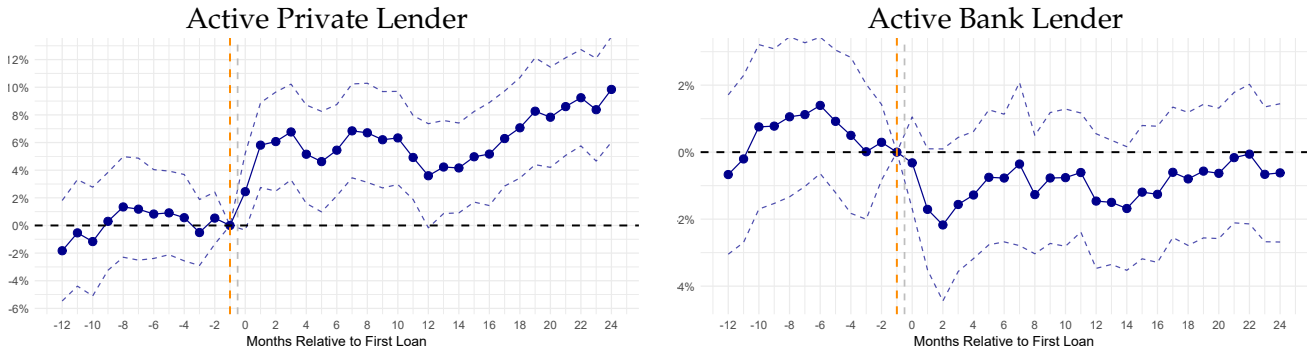


Figure 2. The panels show the top 10 private debt providers over 2006–2023 period. The left panel focuses on Private Equity deals, including Buyout/LBO and PE Growth/Expansion, while the right panel focuses on Pure Debt deals, including Debt – General and Debt – Acquisition (as defined in PitchBook). Providers are ranked by their share of deals financed. Only deals involving companies in the Nielsen dataset are included. Loans issued by different private debt entities or BDCs under the same asset manager are reported separately and not aggregated at the manager level.

Panel A: Sales



Panel B: Product Entry Rates



Panel C: Store Entry Rates

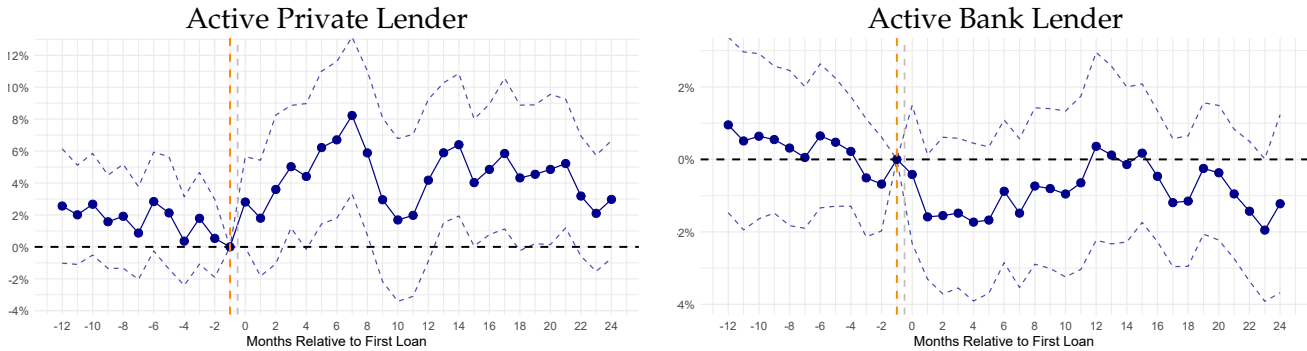


Figure 3. The Dynamic Effects of Access to Private Lenders and Banks. This figure plots the coefficient estimates of Equation (1). In each panel, the left and right-hand figures reports results with *ActivePrivate* and *ActiveBank* as the independent variables, respectively. $t = 0$ indicates the month when the treated firm first obtained a loan from a private lender (bank). The estimates measure the difference in the outcome variable between treated firms and matched controls relative to the reference period, the month before the loan. In Panel A, the estimates represent percent changes in total sales, obtained by the transformation $100(e^{\beta} - 1)$ where β is the coefficient of Equation (1) with the outcome variable in log levels. Standard errors are adjusted for the coefficient transformation using the Delta method. In panels B and C, the estimates represent percentage point changes in product entry rate and store entry rate, respectively. Standard errors are double clustered at the firm and month-year levels. The dashed lines indicate 95% confidence intervals.

Appendix

Private Debt Financing and Product Market Expansion

Sergio H. Rocha Davide Sinno

Table IA.1. Number of Active Loans: Banks versus Private lenders. This table reports the coefficients from the estimation of Equation (1) and Equation (2). The dependent variables are the log of total sales (multiplied by 100) and sales-weighted entry rates. *Total sales* is the monthly total revenues generated by a firm's products. *Product Entry Rate* is the ratio of sales generated by new products to a firm's total sales. We consider a product new during the 6 months with recorded sales in the dataset. *Store Entry Rate* is the ratio of revenues generated in stores where the firm recently entered to its total sales. We consider store entry by a firm recent during the first 6 months with recorded sales by a firm in a store. Entry rates are expressed in percentage points. *Number of Active Lender* is the count of total outstanding loans in a given month. *Number of Active Banks* and *Number of Active Privates* are counts of outstanding loans with banks and private lenders, respectively. The sample consists of firm-month-level observations of treated firms matched to counterfactual controls. Treated firms are those with loans reported in the data between 2007 and 2022. Control firms are those without any loan recorded during the sample period. Each treated firm is matched to a single counterfactual based on total sales, sales growth and number of products, modules, stores, and counties at the month prior to the first loan of the treated firm. A treated-control group is defined as a *cohort* and the sample is a stack of cohorts. See Section 3.3.1 for details of the matching procedure, and Section 3.2 for details on variable construction. *t*-statistics are reported in parentheses. Standard errors are two-way clustered by firm and month-year. †, *, **, and *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% levels, respectively.

	<i>Dependent variable:</i>					
	Sales		Product Entry Rate		Store Entry Rate	
	(1)	(2)	(3)	(4)	(5)	(6)
log(1 + Number of Active Lenders)	34.37 (6.65)***		-0.48 (-1.44)		-0.90 (-2.57)*	
log(1 + Number of Active Privates)		23.35 (2.25)*		4.48 (6.71)***		1.20 (2.05)*
log(1 + Number of Active Banks)		27.99 (3.44)***		-3.18 (-7.08)***		-1.74 (-3.82)***
Firm-Cohort FE	Y	Y	Y	Y	Y	Y
Month-Year-Cohort	Y	Y	Y	Y	Y	Y
Observations	288,234	288,234	288,234	288,234	288,234	288,234
Adjusted R ²	0.82	0.82	0.35	0.35	0.43	0.43

Note:

† p<0.1; * p<0.05; ** p<0.01; *** p<0.001

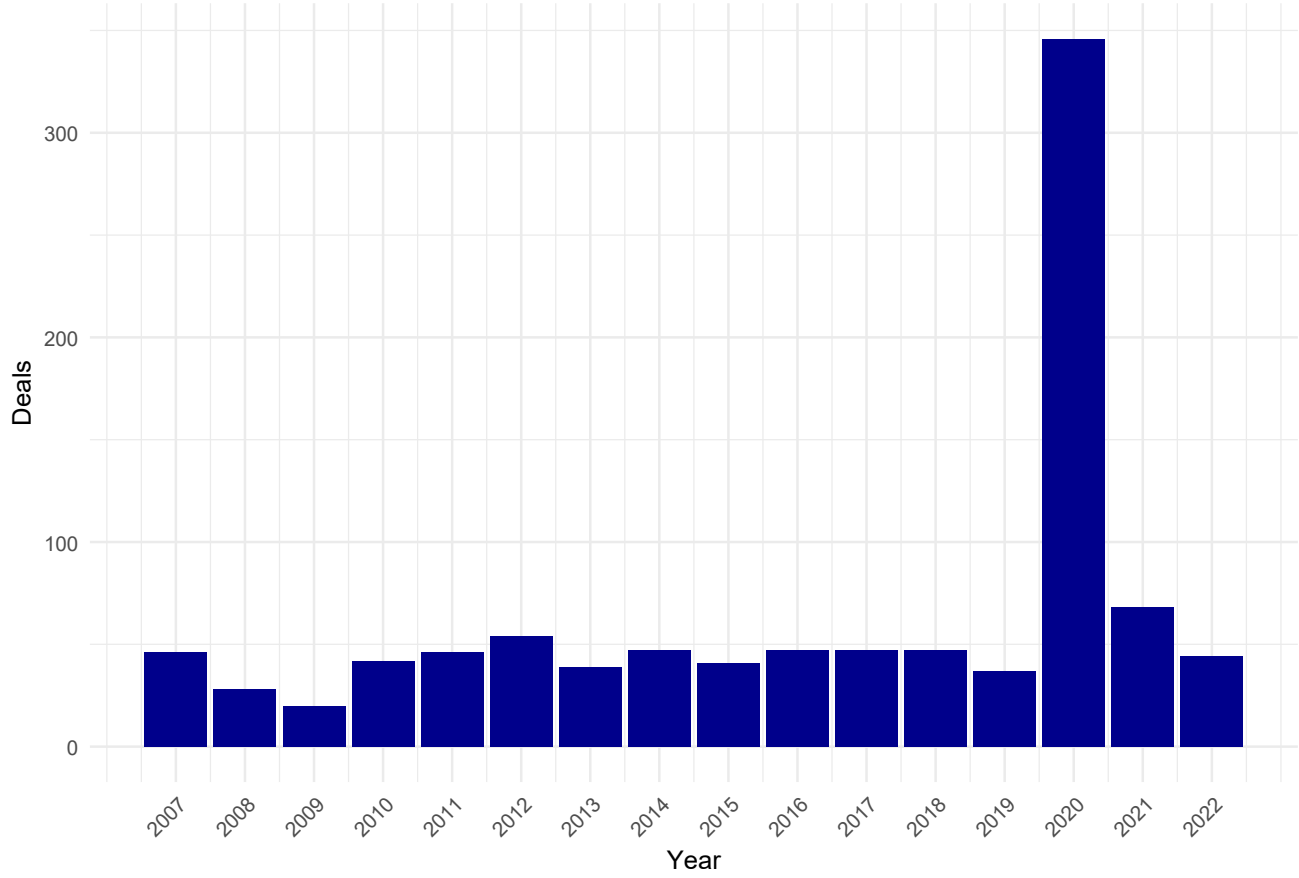


Figure IA.1. This figure shows the distribution of 999 matched deals in our baseline PitchBook - Nielsen sample across years. See sections 3.3 and 3.3.1 for details on the matching procedure.

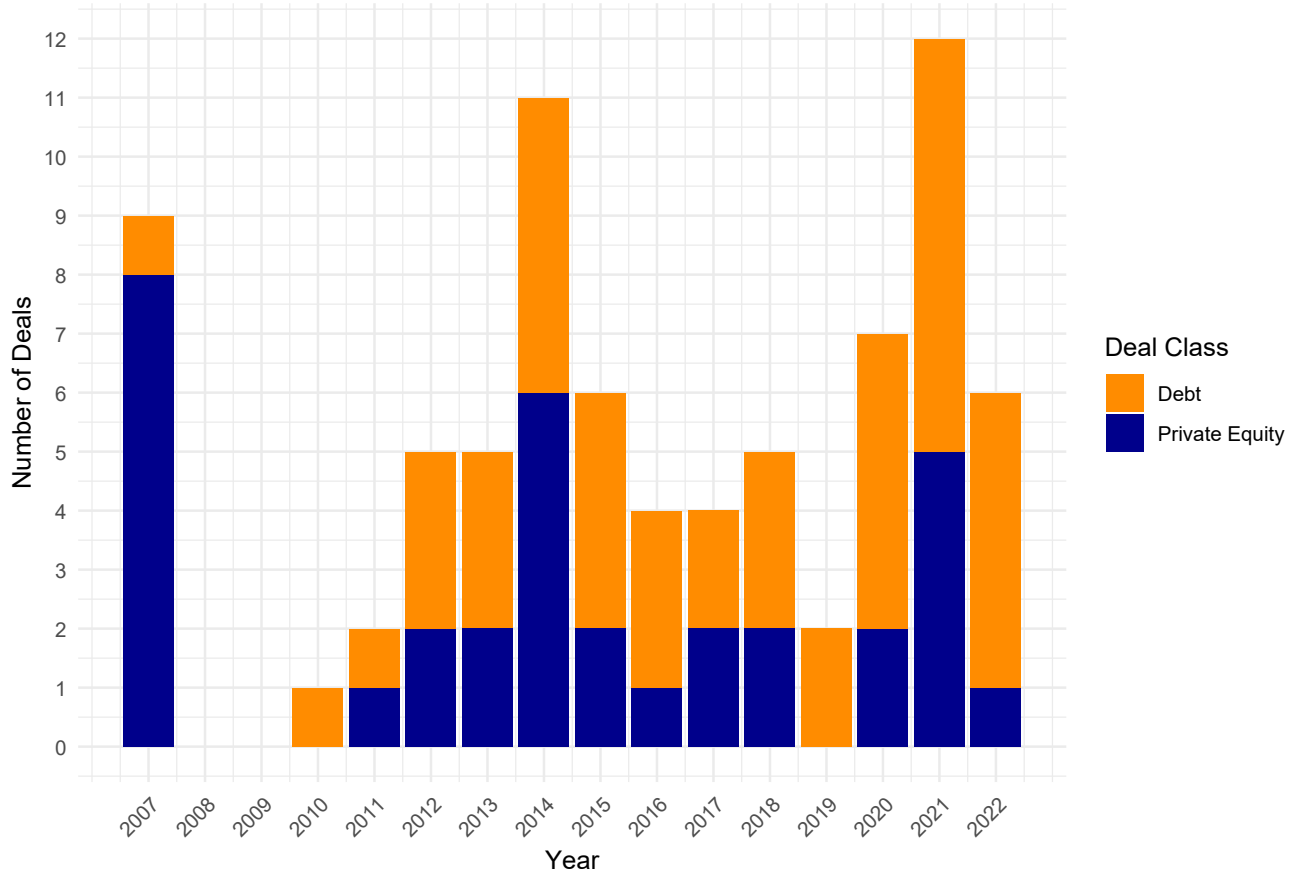


Figure IA.2. This figure shows the distribution of 79 matched deals in our firm-deal matched sample across years. Each deal corresponds to a loan of either “debt” or “private equity” class with both banks and private lenders as creditors that was matched to a loan of the same class, made in the same month, but with only banks as creditors. For each firm with a loan reported in PitchBook, only the first deal of each class is considered. See sections 3.3 and 3.3.2 for details on the matching procedure.

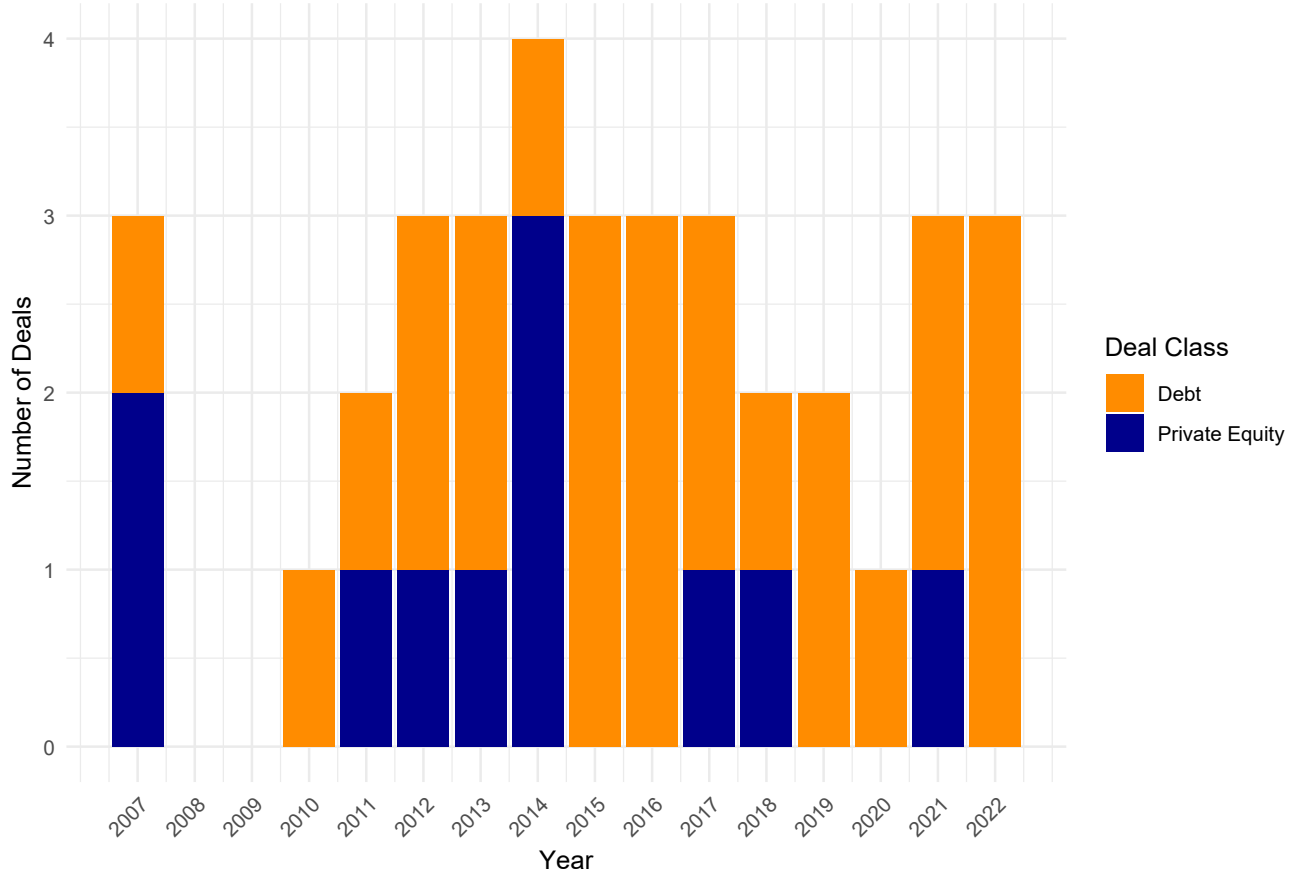


Figure IA.3. This figure shows the distribution of 36 matched deals in our single-deal matched sample across years. Each deal corresponds to a loan of either “debt” or “private equity” class with both banks and private lenders as creditors that was matched to a loan of the same class, made in the same month, but with only banks as creditors. For each firm with a loan reported in PitchBook, only the first deal is considered. See sections 3.3 and 6.2 for details on the matching procedure.

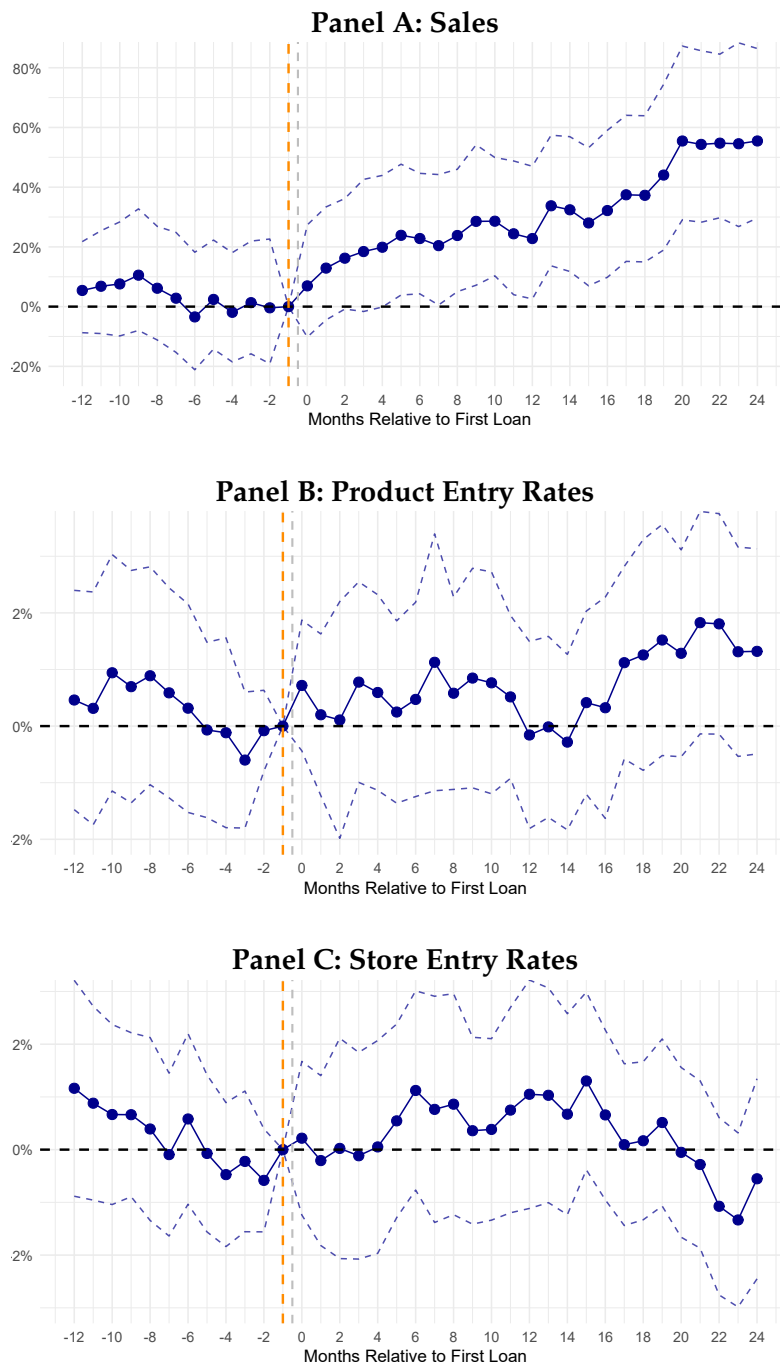


Figure IA.4. The Dynamic Effects of Access to Any Lenders. This figure plots the coefficient estimates of Equation (1). In each panel, the figures reports results with *ActiveLender* as the independent variables. $t = 0$ indicates the month when the treated firm first obtained a loan either a private lender or a bank. The estimates measure the difference in the outcome variable between treated firms and matched controls relative to the reference period, the month before the loan. In Panel A, the estimates represent percent changes in total sales, obtained by the transformation $100(e^{\beta} - 1)$ where β is the coefficient of Equation (1) with the outcome variable in log levels. Standard errors are adjusted for the coefficient transformation using the Delta method. In panels B and C, the estimates represent percentage point changes in product entry rate and store entry rate, respectively. Standard errors are double clustered at the firm and month-year levels. The dashed lines indicate 95% confidence intervals.