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ABSTRACT

We compare the lending technology of direct lenders, banks, and finance companies using a unique data set on secured borrowing by the universe of U.S.-based private middle market firms. The borrowers of direct lenders are distinct relative to those of traditional lenders; they are younger, more likely to be in intangible capital industries, and more likely to be located in the biggest cities in the United States. These differences reflect the focus of direct lenders on private equity-owned firms; direct lenders have negligible impact in industries and cities with low private equity presence. The lending technology of direct lenders is distinct from banks: they have almost no branch network, they are geographically distant from borrowers, they write collateral claims more focused on the continuation value of firms after a default, and they have a higher degree of specialization in certain industries. Direct lenders and private equity sponsors match on industry specialization more strongly than geographic proximity. The findings suggest that direct lenders are not a general substitute for traditional lenders in middle market business lending, but they are instead specialized lenders focused on a particular segment of the U.S. economy with a distinct lending technology.

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The stunning rise of direct lenders–non-depository financial firms that are structured as private credit funds or business development corporations–raises fundamental questions concerning the economics of financial intermediation. Direct lenders have seen assets under management increase from below \$200 billion prior to the Great Recession to over \$1.6 trillion in the U.S. by 2024.[1] A common argument in the financial industry is that direct lenders are a close substitute for banks, displacing them in middle market lending.[2] If true, the substitution away from banks and toward direct lenders by middle market borrowers would call into question a long-standing body of research.[3] Scholarship in financial intermediation argues that deposit-financed banks are best positioned to do information-sensitive lending due to their comparative advantages in information and monitoring technologies, liquidity provision, and loan sourcing (e.g., Diamond (1984); Berger and Udell (1995); Diamond and Rajan (2001); Kashyap, Rajan and Stein (2002); Berger, Miller, Petersen, Rajan and Stein (2005); Degryse and Ongena (2005)).

The goal of this study is to compare the lending technology of direct lenders with those of banks and finance companies. Even basic questions on this topic remain largely unexplored. What type of firms borrow from direct lenders versus traditional lenders? Are direct lenders, in general, a substitute for banks and finance companies? Are there obvious differences in the lending technology of direct lenders versus those of banks and finance companies?

A central challenge in answering these questions is data availability. Middle market firms are mostly private companies with little public information on the sources of their financing, and the portfolios of direct lenders are largely unobservable in readily available data sources. Furthermore, there are few data sets that jointly track loans made by banks, finance companies, and direct lenders, thereby limiting the ability to directly compare the borrowers of these distinct intermediaries.

This study builds a novel dataset to meet this challenge. The backbone of the dataset is the

[1] According to Preqin, total North American private credit fund assets under management were \$170 billion in 2007 and \$1.242 trillion in 2024. According to the LSTA, total assets of Business Development Corporations were below \$30 billion in 2007 and \$438 billion in 2024. A companion paper Jang, Kim and Sufi (2025) shows using regulatory data that total assets under management for private credit in the United States are closer to \$2 trillion as of 2024

[2] For example, Morgan Stanley notes that "the direct lending market has grown, but we firmly believe that growth is defensible. At the macro level, direct lending has effectively stepped in to fill the void left by banks that have generally retreated from mid-market lending post-crisis." Similarly, PGIM, Inc emphasizes that "direct lending has grown dramatically over the last 10 years and we believe will likely continue . . . With the GFC and Dodd-Frank reform, enhanced rules and regulatory requirements decreased banks' ability and willingness to issue loans to middle-market companies."

[3] Middle market firms are usually defined as firms with between 50 and 1000 employees or annual revenue between \$10 million and \$1 billion.

National Establishment Time Series (NETS) database produced by Walls & Associates from Dun & Bradstreet records. This dataset covers the near-universe of business establishments in the United States, which allows for the construction of a data set of middle market firms (e.g., Neumark, Wall and Zhang (2011)).[4] The NETS dataset is matched to Business Development Corporation (BDC) investments, private credit investment information from PitchBook, and Uniform Commercial Code (UCC) filings, which are filings a creditor submits to a state to publicly declare a security interest in a borrower's collateral (e.g. Gopal and Schnabl (2022)). Data from PitchBook and Preqin are used to identify which lenders are direct lenders, and which borrowers are owned by a PE sponsor. Finally, the dataset is augmented with a broader measure of firms owned by a PE sponsor, which is constructed from information available on the internet using Google's Vertex Artificial Intelligence platform.

There are a few advantages of this data set relative to the existing literature. First, because the backbone of the data set is the universe of all U.S. businesses, the data set allows for measurement of the firms that do and do not borrow from direct lenders. This is crucial to understanding the overall penetration of direct lenders across the U.S. economy, and we believe many of the statistics we provide in this regard are new to the literature. Second, the UCC filings offer a more comprehensive view of the borrowers of direct lenders relative to data on Business Development Corporations (BDCs) or PitchBook. The data advantage of UCC filings is especially large for first lien loans to lower middle-market firms, which are the most similar type of direct loan compared to a finance company or bank loan. Third, the data set contains a more comprehensive measure of the firms owned by a PE sponsor using the Google Vertex AI platform to leverage all of the information on the internet to discover whether a firm has received a PE investment. Private equity is a crucial part of the direct lending strategy; accurate measurement of private equity is an important part of any analysis of direct lenders.

The data set shows that while direct lending has grown substantially over the past fifteen years, the fraction of non-financial, middle market, U.S. companies that borrow from direct lenders is still small relative to finance companies and banks. As of 2022, the share of U.S. middle market non-financial companies with a direct loan as measured by UCC filings is 2.5% when weighted by employment; the analogous shares for banks and finance companies are 41.3% and 19.3%, respectively. Under a broader definition of whether a firm receives an investment from the private credit industry in general, which includes any investment by BDCs and PitchBook investments by

[4]Throughout the analysis, the "middle market" is defined as firms employing between 21 and 1000 workers.

private credit firms, the employment-weighted share of middle market firms with a private credit investment is 3.5%, still substantially below banks and finance companies.

Middle market firms that borrow from direct lenders are distinct from those that borrow from banks and finance companies, and the differences are quantitatively large. The borrowers of direct lenders tend to be younger, more likely to be in intangible capital-intensive industries such as business services and software, more likely to be in the largest cities in the United States, and larger on average in terms of total employment. For example, 20% of the borrowers of direct lenders are in the "Professional, Scientific, and Technical Services" industry (3-digit NAICS of 541), compared to only 12% of the borrowers of banks and finance companies. Examining city size, we find that 29% of the borrowers of banks and finance companies are located in the top 10 largest cities in the United States by population compared to 40% of those of direct lenders.

To quantify the differences in the borrower portfolios of banks, finance companies, and direct lenders, we use a Mahalanobis distance measure, which measures the difference in portfolios based on key characteristics and their covariance-variance structure. The Mahalanobis distance measure between the borrower portfolios of banks and finance companies is 0.16. In contrast, the distance between the portfolios of direct lenders and banks is 0.80 and that between direct lenders and finance companies is 0.79.

These large differences in the borrower portfolios of banks and finance companies versus direct lenders are completely explained by the focus of direct lenders on firms owned by PE sponsors. Two measures of whether a firm is owned by a PE sponsor are used in the analysis: a narrow measure for which PitchBook is used to identify PE ownership of a given firm in the NETS dataset, and a broader measure for which Google Vertex AI is used to search the internet for any evidence that a given firm is owned by a PE sponsor. According to the broader measure, PE-owned firms comprise 75% of the borrowers of direct lenders compared to 17% for banks and 16% for finance companies.

At the lender-level, mean age of borrowers for direct lenders is a full standard deviation lower relative to banks and finance companies, mean industry asset intangibility is almost two standard deviations higher, and mean city population is almost a full standard deviation higher. However, when the regression framework controls for the mean share of firms that are owned by a PE sponsor in the portfolio, all of these differences between direct lenders and traditional lenders disappear. The large differences in portfolio borrower characteristics reflect the direct lenders' heavy focus on PE-owned firms.

The fact that direct lenders focus so heavily on PE-owned firms is widely understood from both survey evidence from the academic literature (e.g., Block, Jang, Kaplan and Schulze (2024)) and industry research. What is less appreciated, however, is that the focus of direct lenders on PE-owned firms implies a particular and limited sphere of economic impact by direct lenders relative to traditional lenders. This is due to the fact that private equity, even over the long run, primarily has engaged firms in specific industries and specific geographies.

To illustrate this point, we calculate the share of firms owned by a PE sponsor in 2007 in a given industry and in a given city. We show that the 2007 distribution of private equity penetration across industries and cities predicts the 2022 distribution of private equity penetration with a high degree of statistical power. For the 15-year sample period, there is strong persistence in PE investments across industries and geographical areas of the United States.

Using this persistent relationship in private equity penetration, we show the 2007 distribution of the share of firms owned by private equity across cities and industries strongly predicts the share of firms in 2022 that receive a loan from a direct lender in a given industry-city cell. The distribution of private equity also predicts the increase in the share of firms receiving a loan from direct lenders. In fact, for industry-city cells where PE ownership is limited in 2007, there is almost no increase in the presence of direct lenders. In other words, there are large parts of the U.S. economy where private equity is largely absent; these segments of the economy are serviced by banks and finance companies, whereas direct lenders have made almost no inroads.

The lending technology of direct lenders is uniquely well positioned to fund PE-owned firms, and direct lenders have not penetrated the non-PE owned segments of the U.S. economy. Why? An important clue lies in the lack of a branch network. Direct lenders are overwhelmingly concentrated in the largest cities in the U.S. economy, with little to no branch presence elsewhere. The median distance between a direct lender and a portfolio company is 1,100 miles; the median distance between a bank and one of its borrowers is 30 miles. A large body of research establishes the importance of geographic proximity for information-sensitive bank lending (e.g., Petersen and Rajan (1995), Degryse and Ongena (2005); Mian (2006); Alessandrini, Presbitero and Zazzaro (2009); Agarwal and Hauswald (2010)). Direct lenders face this major constraint in their lending allocation, which may explain why they rely on PE sponsors, who themselves devote significant resources to sourcing deals (e.g., Gompers, Kaplan and Mukharlyamov (2016)).

Another key difference for the lending strategy of direct lenders is a heavy reliance on so-called "blanket liens". Unlike liens on specific types of physical capital, the value of a blanket lien is more closely linked to the going-concern value of a company that defaults (e.g., Lian and Ma (2021), Caglio, Darst and Kalemli-Özcan (2021)). Hence, the value of a blanket lien to a lender depends on the continuation value of the overall firm in the event of default as opposed to the liquidation value of separable assets. As of 2022, the mean share of loans secured by blanket liens for direct lenders is 79%; it is less than 15% for banks and 3% for finance companies. Banks are more likely to place a lien on current assets, such as accounts receivable and inventory, and fixed assets, such as equipment and vehicles. These findings suggest that a key relative advantage of direct lenders over banks is an ability and willingness to bet on the continuation value of a firm in case of default, which is an important skill when lending to PE-owned firms.

Further support for the idea that direct lenders are more willing to bet on the continuation value of a firm after default is their high degree of industry specialization. Blickle, Parlatore and Saunders (2023) show that banks concentrate their lending disproportionately in a few industries, consistent with the importance of a bank's industry-specific knowledge. Using similar measures of industry specialization, this study shows that direct lenders are significantly more industry-specialized than banks. The magnitude is large; relative to banks, direct lenders allocate 10 percentage points more of their total lending in the industry in which they have the largest share.

Complementary evidence comes from an analysis of how PE sponsors choose direct lenders. Private equity investors often develop deep industry expertise that enables them to add value through "operational engineering" (Kaplan and Stromberg, 2009). We find that geographic proximity to the direct lender matters far less than congruence of the industry focus of the direct lender. PE sponsors and direct lenders match strongly on shared industry expertise, suggesting that industry specialization is an important part of the relationship between the two.

Related literature

This study is most closely related to the substantial body of recent research on private credit (e.g., Acharya, Cetorelli and Tuckman (2024); Albuquerque and Zawadowski (2025); Aldasoro and Doerr (2025); Avalos, Doerr and Pinter (2025); Boni and Manigart (2023), Block, Jang, Kaplan and Schulze (2024); Cai and Haque (2024); Chernenko, Ialenti and Scharfstein (2025); Davydiuk, Erel, Jiang and Marchuk (2024a); Davydiuk, Marchuk and Rosen (2024b); Davydiuk, Marchuk and Rosen (2024c); Ellias and de Fontenay (2025); Erel, Flanagan and Weisbach (2024); Fritsch, Lim, Montag and Schmalz (2022); Gonzales-Uribe and Balloch (2021); Haque, Jang and Wang (2025b); Haque, Mayer and Stefanescu (2025a); Ivashina (2025); Jang (2025); Jang and Kim (2025); Jang, Kim and Sufi (2025); Levin and Malfroy-Camine (2025); Loumioti (2022); Munday, Hu and Zhang

(2018); Rintamäki and Steffen (2025); Robinson and Wallskog (2025); Suhonen (2024)). To the best of our knowledge, this is the first study to measure the set of firms that borrow from direct lenders using UCC filings. Given the commonality of this filing across banks, finance companies, and direct lenders, the UCC filings allow us to directly compare the lending strategies of these different intermediaries. Section 2.5 below compares the use of UCC filings versus BDC filings or data from commercial data providers, and it provides evidence that the UCC filings data are more comprehensive. This study is also the first, to our knowledge, to measure the share of firms that borrow from direct lenders across the entire United States, which we are able to do given the match between NETS and measures of direct lending.

Block, Jang, Kaplan and Schulze (2024) survey a set of 191 private debt investors and find that 78% of firms borrowing from a U.S.-based private debt investor are owned by a private-equity sponsor. This study finds a similar fraction using the UCC filings matched to NETS, and it emphasizes broader implications of the focus of direct lenders on PE-owned companies. Davydiuk, Marchuk and Rosen (2024b) use BDC data and emphasize that the portfolio firms of BDCs are more likely to be in high-tech industries, which is related to our finding that direct lenders focus disproportionately on intangible capital-intensive industries. The use of NETS combined with UCC filings allows us to compare these figures directly with the borrowers of banks and finance companies, and it also allows us to show that direct lenders have a large presence in industries traditionally targeted by PE sponsors.

The study by Haque, Mayer and Stefanescu (2025a) compares loans by direct lenders and banks for the same borrowers, which they call "dual" borrowers, and they find that banks often provide a line of credit while direct lenders provide riskier and more junior term loans. Chernenko, Erel and Prilmeier (2022) focus on a sample of 750 publicly traded middle-market firms, and they find that non-banks lend to lower EBITDA and more levered firms. In a sample of loans for which direct lenders are present either as a lead arranger or as a participant lender, Jang (2025) compares the loans arranged by banks versus direct lenders. The focus of Jang (2025) is on the terms of the loan contracts and monitoring intensity of direct lenders versus banks. The focus here is complementary: this study shows differences between direct lenders loans and bank loans in terms of geography and industry focus, use of collateral, and distance to borrowers.

A large body of literature examines the effects of private equity on firms, both in terms of real outcomes and capital structure.[5] Related to the latter, substantial research has documented the

[5]For research on real effects, see e.g., Bernstein and Sheen (2016), Boucly, Sraer and Thesmar (2011), Davis,

economic benefits of repeated relationships between lenders and PE sponsors, primarily in bank-syndicated lending (e.g. Bernstein, Lerner and Mezzanotti (2019); Demiroglu and James (2010); Haque and Kleymenova (2023); Hotchkiss, Smith and Strömberg (2021); Ivashina and Kovner (2011)). In the direct lending market, Jang (2025) shows that close relationships between direct lenders and PE sponsors help sustain credit during periods of stress. To the best of our knowledge, this study is the first to examine what drives direct lenders and PE sponsors to form relationships in the first place. We show that direct lenders tend to match with PE sponsors more strongly on industry specialization than on physical proximity. From a measurement perspective, to the best of our knowledge, this is the first study to utilize machine learning techniques and information on the internet to measure firms that owned by a PE sponsor.

1 Direct Lending: Background and Measurement

Private credit is a major asset class in which non-depository institutions provide non-publicly traded debt financing to privately-held middle market firms.[6] The intermediaries are usually structured either as a private credit fund–which is a closed-end investment vehicle not registered as an investment company–or as a business development corporation (BDC)–which is a closed-end investment company created through the Small Business Investment Act of 1980.[7]

Direct lending refers to a specific loan strategy within the broader private credit fund universe. While definitions are in flux, direct lending typically refers to a strategy in which the lender provides first-lien senior secured debt financing to middle-market firms. It is also often described as "cash-flow-based lending" as opposed to lending against a specific asset. Alternative private credit strategies include mezzanine debt financing, distressed debt financing, asset-backed credit financing (such as aviation financing and securitization strategies), and investments in the broadly syndicated loan market. Based on Preqin estimates and BDC filings, private credit assets under management grew from under $200 billion before the Great Recession to over $1.6 trillion in the U.S. by 2024.

Haltiwanger, Handley, Jarmin, Lerner and Miranda (2014), Davis, Haltiwanger, Handley, Lerner, Lipsius and Miranda (2021), Eaton, Howell and Yannelis (2020), Fracassi, Previtero and Sheen (2022), Gornall, Gredil, Howell, Liu and Sockin (2025), Gupta, Howell, Yannelis and Gupta (2021), Lerner, Sorensen and Strömberg (2011), Mittal (2025). For research on capital structure, see e.g., Axelson, Strömberg and Weisbach (2009), Axelson, Jenkinson, Strömberg and Weisbach (2013), Cohn, Hotchkiss and Towery (2022), Haque (2022), Haque, Jang and Mayer (2023b), Haque, Mayer and Wang (2023a), Kaplan and Stein (1993), Malenko and Malenko (2015), Shive and Forster (2023).

[6] See Cai and Haque (2024) for an excellent overview of the private credit industry.

[7] BDCs can then be classified as publicly traded, non-publicly traded, or privately offered.

In a companion paper that uses the regulotry Form PF data, Jang, Kim and Sufi (2025) estimates an even larger figure, closer to $2 trillion just for corporate private credit.

The primary focus of this study is on direct lending. Direct lending is the largest strategy within the private credit universe, with estimates suggesting a share of 50% (e.g., Cai and Haque (2024)). It is also the lending strategy that is closest to the relationship-based, information-sensitive business lending that has been historically the purview of deposit-financed commercial banks. As such, direct lending by non-deposit financed intermediaries represents the biggest departure from theories that emphasize the complementarity between deposit-taking and relationship-based, information-sensitive lending in the literature. To assess whether private credit is a substitute for bank lending, we believe direct lending to middle-market firms is the most important segment to explore.

Measuring the middle-market firms that obtain such relationship-based, information-sensitive loans from direct lenders is a serious challenge. Existing studies have mainly relied on two sources of data. The first source is BDC Securities and Exchange Commission (SEC) filings, which are required given that BDCs are registered investment companies. The main advantage of BDC data is that the investments in portfolio companies are publicly available. However, in terms of assets under management, BDCs represent only a limited fraction of the broader private credit universe. As of 2024, BDCs held about $438 billion in assets, according to the Loan Syndication Trading Association.[8] According to Preqin, which excludes BDCs, North American private credit fund assets totaled $1.24 trillion. In other words, BDCs account for roughly one quarter of the combined total of private credit assets when both are considered together. Historically, BDCs' share was even smaller, below $30 billion in 2007 compared to $170 billion in North American private credit fund assets at the time. Furthermore, some of the investments made by BDCs are not the relationship-based information-sensitive loans to middle market firms that can be viewed as a direct substitute for bank loans. For example, BDCs make substantial investments in the broadly syndicated loan market (see Figure IA5 in Chernenko, Ialenti and Scharfstein (2025)). BDC investments are often mezzanine, hybrid, or even equity investments (e.g., Davydiuk, Erel, Jiang and Marchuk (2024a); Robinson and Wallskog (2025)).

A second source of data used in the existing literature is from the commercially-available data collected by PitchBook. PitchBook data is also heavily tilted toward BDC investments. For example, Haque, Mayer and Stefanescu (2025a) report that, out of about 17 thousand private credit loans in their PitchBook sample, approximately 11 thousand involve a BDC. This overlap reflects

[8] Please see "BDC Quarterly Wrap: 4Q24" at https://www.lsta.org/news-resources/bdc-quarterly-wrap-4q24/.

how PitchBook builds its coverage: the platform employs a vast web-crawling infrastructure that searches over online sources, including news articles, press releases, company websites, and regulatory filings, to identify private market deals.[9] Because this process depends on public visibility, PitchBook likely captures more transactions involving larger and more transparent firms, such as publicly listed firms, firms backed by well-known sponsors, or lenders subject to public reporting requirements such as BDCs.

The data set constructed for this study allows for a direct comparison of borrowers that are in the BDC and PitchBook universe compared to borrowers that obtain a loan with a UCC filing recorded from a direct lender. As shown in Section 2.5, there are significantly fewer borrowers in the BDC and PitchBook universe relative to UCC filings, and the borrowers in the BDC and PitchBook universe are significantly larger compared to borrowers with UCC filings from a direct lender. As discussed below, we believe the presence of a UCC filing is a more comprehensive and more accurate measure of the middle-market borrowers that obtain relationship-based information-sensitive loans from a direct lender.

2 Data

2.1 National Establishment Time Series data

The primary firm-level data source for our analysis is the National Establishment Time Series (NETS) database, compiled by Walls & Associates from Dun & Bradstreet records. NETS provides comprehensive coverage of business establishments across the United States, enabling the construction of a detailed dataset of middle-market firms. The dataset spans from 1990 to 2022 and includes approximately 87 million establishments. At the establishment level, NETS records include key information such as the number of employees, sales, age, credit rating ("PAYDEX" score),[10] industry classification (NAICS and SIC), and geographic location (address, city, state, and ZIP code).

To construct our firm-level sample, we use the unique nine-digit identifier assigned by Dun & Bradstreet to each establishment, known as the *dunsnumber*, and the related *hqduns* field, which

[9]See https://pitchbook.com/help/pitchbook-research-process.

[10]A PAYDEX score, provided by Dun & Bradstreet, is a business credit rating that evaluates a company's financial reliability based on its punctuality in paying trade creditors. Scores range from 1 to 100, with higher values reflecting lower credit risk.

identifies the establishment's headquarter. Both fields are initially assigned by Dun & Bradstreet. However, many instances exist where an establishment listed as a headquarter (*hqduns*) reports another *hqduns* as its own parent. To address this, we apply the parent roll-up strategy described in Section 2.3.3 of Crane and Decker (2020), aggregating all linked establishments, directly or indirectly, under the highest-level headquarter that reports itself as its own *hqduns*. Applying this procedure to the 2022 NETS data aggregates 37,413,572 establishments into 35,101,180 firms.

We further refine the sample by excluding firms operating in government (3-digit NAICS 921–928), religious and non-profit organizations (3-digit NAICS 813), educational institutions (3-digit NAICS 611), financial services (2-digit NAICS 52), and real estate (2-digit NAICS 53). We also remove any firm in the NETS data set that has 2 or few employees. This latter restriction is motivated by Crane and Decker (2020) who argue that there is considerable imputation of key variables for small firms in the NETS data.[11] With these restrictions, the sample of firms as of 2022 in the NETS data includes 7,656,066 observations.

For this sample, we also merge to Compustat to obtain information on whether the firm is publicly traded. The NETS data itself has an indicator variable for whether a firm is publicly traded, and this is highly correlated with whether the firm is in Compustat. We create an public firm indicator variable which is equal to one if the firm can be matched with Compustat or if NETS indicates the firm is public.

The final sample for most of the analysis in this paper is private middle-market firms, which are defined as firms that are not publicly-traded, and that have between 21 and 1,000 employees. This final sample includes 468,784 firms as of 2022. Most standard definitions of middle-market firms based on employment include firms with 50 to 1,000 employees; we utilize a more expansive definition to capture more of this market.

While NETS provides extensive coverage, several caveats should be noted. Sales data are often unreliable due to high rates of imputation and are therefore excluded from our analysis. Employment data, however, are generally reliable when analyzed using employment bins or ranges. As noted by Crane and Decker (2020), NETS is "reasonably representative of U.S. business activity in the static cross section," with strong correlations to official data in terms of size, industry, and geography, particularly when smaller establishments are excluded. Follwing their advice, our analysis focuses on middle-market firms and cross-sectional patterns across industry and geographic cells, rather

[11] Given that most of our analysis focuses on middle market firms, which are defined as firms between 21 and 1000 employees, this restriction does not materially affect the analysis.

than firm-level time-series dynamics. In line with Crane and Decker (2020)'s recommendation to study low-frequency dynamics, the only temporal component we consider is the long-term change (over ten years) in private equity penetration across these cells.

2.2 Uniform Commercial Code filings

Our main data source for lending is UCC filings, which contain detailed information on non-real-estate secured loans across the United States. We obtain UCC filings from a commercial vendor covering all 50 U.S. states and Washington, D.C., from 2006 to 2022. Each filing record includes the filing date, borrower and lender information such as name, location (state, city, ZIP), and *dunsnumber* (which can be readily linked to NETS), and detailed collateral descriptions. Collateral information is classified across 41 categories, which we group into four broad catagories: fixed asset liens (e.g., equipment, fixtures, buildings, vehicles), current asset liens (e.g., accounts receivables and inventory), blanket liens, and liens that otherwise cannot be easily placed into one of these three categories (e.g., a lien on "products and proceeds," "unspecified," or "other"). The collateral code information is also missing for a number of observations in the UCC filings. The blanket lien designation is important in the analysis, and we discuss this in more detail in Section 5.2.

Gopal and Schnabl (2022) provide a detailed description of the UCC data and show that it covers a large share of small business lending by banks and finance companies. We examine whether the extensive coverage of UCC filings extends to middle-market lending. Using syndicated loan deal data from Dealscan and private credit deal data from both PitchBook and Jang (2025), we find that UCC filings capture nearly all borrowers across both broadly syndicated and direct lending markets. The filings also reliably identify lead lenders – both banks and direct lenders – indicating that UCC data provide comprehensive coverage of middle-market borrowers' primary lending relationships, especially in direct lending. Appendix A provides a detailed summary of this investigation.

We classify lenders into three main categories: a direct lender, bank, or finance company. Direct lenders are primarily identified using lists of U.S. private credit funds from PitchBook and Preqin, supplemented with keyword searches. Banks and finance companies are identified using NAICS codes from NETS, further augmented with keyword searches and a list of the largest known banks and finance companies.

We retain filings that reflect ongoing lending relationships, including originals, amendments, continuations, assignments, subordinations, partial releases, and corrections, while excluding terminations and full releases, following Gopal and Schnabl (2022). Filings are then merged with NETS at the establishment level using *dunsnumber* before aggregating at the firm level. To identify a borrower's active lender, we consider filings over the previous five years, reflecting the requirement that lenders renew security interests every five years. Detailed methods for processing and classifying lender types from the UCC filings data are documented in Appendix A.

Combining UCC filings with NETS yields a uniquely comprehensive view of middle-market lending in the United States. The dataset allows us to examine the full universe of non–real-estate secured loans across direct lenders, banks, and finance companies, with rich information on collateral types and the geographic distribution of lenders.

2.3 Measuring PE ownership

As shown in the survey evidence of Block, Jang, Kaplan and Schulze (2024), direct lenders primarily lend to PE-sponsored firms. Therefore, any study of direct lender activity using administrative data must utilize the best possible data on firms owned by a PE sponsor in NETS. We identify PE ownership using two sources: PitchBook and a custom dataset we constructed using the Google Vertex AI Platform. PitchBook provides detailed information on investor identities and deal characteristics and is widely recognized as one of the most comprehensive data sources on private capital deals in the literature. Using PitchBook, we identify firms that received private equity or venture capital financing and extend our coverage of private credit financing (e.g., Haque, Mayer and Stefanescu (2025a)).

PitchBook's coverage is extensive, but we have found it quite difficult to match the data to NETS. Crucially, to ensure accuracy, our matching methodology relies on exact or near-exact matches between company identifiers in the NETS data set and entries in PitchBook's proprietary database. Our dataset provides both company names and addresses for matching, which should theoretically strengthen match accuracy. However, our manual validation revealed that even when company names matched identically between our dataset and PitchBook's web version, the registered addresses often differed. These matching difficulties are compounded when firms use different legal names, have changed their registered addresses over time, or operate under parent company structures. Our manual validation confirms that the limitation arises not from incomplete PitchBook coverage—which remains extensive and detailed—but from the rigidity of structured field-matching algorithms when applied across heterogeneous datasets. We provide more details on this issue in

Appendix Section B.2.

The basic idea behind the use of the Google Vertex AI technology is the following: the NETS data contains the name, address, and phone number of every middle market firm. With this information in hand, is it possible to use the information available on the internet to measure whether a given firm was owned by a PE sponsor in some specific time frame? The answer to this question based on our validation exercises is "yes." Specifically, the Google Vertex AI platform is used to measure whether each of the private middle market firms in the 2022 data set was owned by a PE sponsor between 2018 and 2022. It also reports the name and address of the PE sponsor. Appendix Section B.2 discusses this technique and validation exercises in much more detail. It should be noted from the outset that the fraction of private middle market firms that have received a PE investment using this technology (17.2%) is substantially higher than using matches with PitchBook (1.5%). As mentioned above, the low fraction of firms owned by a PE sponsor in NETS using PitchBook is due to difficulties matching PitchBook to NETS, not to issues related to PitchBook coverage.

2.4 Additional data sets

We rely on BDC Collateral to additionally identify firms receiving private credit. Compiled from mandatory SEC filings, the dataset provides each BDC's quarterly portfolio holdings, including company names, investment amounts, security types, and valuations. Due to the SEC's quarterly disclosure requirement, BDCs have been extensively studied in the private credit literature (e.g., Davydiuk, Marchuk and Rosen (2024b)). We use these filings to identify middle-market borrowers receiving BDC financing (both debt and equity investments). Jang and Kim (2025) and Haque, Jang and Wang (2025b) provide detailed descriptions of the BDC Collateral data.[12] All external financing datasets (BDC Collateral, PitchBook, and Compustat) are carefully matched to NETS using firm name, address, and phone number information.

The NETS data set includes a 3-digit NAICS code of every firm that is used to merge with industry-level information from He, Mostrom and Sufi (2024) on share of total capital that is intangible (K_{IT}/K_{TOT}). As described in He, Mostrom and Sufi (2024), intangible capital at the firm level is comprised of R&D related capital, sales and marketing-related capital, and externally acquired

[12]Matching BDC portfolio companies to NETS is a challenge given that it is not easy to retrieve the address of the companies from SEC filings. We use a combination of information from N-2 filings and the Google Vertex AI platform to search for the exact addresses of every firm receiving a BDC investment.

intangible capital. Physical capital includes property, plants, and equipment on the balance sheet. The ratio of intangible capital to total (intangible plus physical) capital is calculated at the firm level, and then the industry-level median is calculated from the firm-level data. It is the median industry-level variable that is used in the analysis below.[13] Also included is the total population of the Core-Based Statistical Area of each firm in the NETS data. These data are collected from the Census. We refer to a CBSA throughout the analysis as a "city."

2.5 Summary statistics and comparison with other data sets

Firm-level and lender-level summary statistics

Table 1 presents summary statistics for both the entire NETS sample (first set of three columns) and the private middle market sample (second set of three columns). The averages of all key variables are shown both equal-weighted and weighted by the employment of the firm. The year is 2022 and the loan and private equity summary statistics represent whether the firm obtained the investment in question in the last five years; that is, between 2018 and 2022.

For the full sample, the UCC filings suggest that almost 8% of firms, when weighted by employment, have a loan by a direct lender at some point between 2018 and 2022. The comparable statistics for banks and finance companies are 47% and 35%, respectively. While direct lenders have increased their presence in the U.S. economy, they still have relationships with far fewer firms than banks or finance companies, and these differences are especially dramatic in the equal-weighted summary statistics. In the private middle market sample, direct lenders have loans to 2.5% of firms when weighted by employment, compared to 41% for banks and 19% for finance companies. Table A2 in the appendix breaks down these averages by detailed employment size category. As shown there, direct lenders also have a presence among larger borrowers with more than 1000 employees. This, however, is not the focus of this study because loans to such large borrowers are unlikely to be the information-sensitive relationship loans that have been historically dominated by deposit-financed banks.

The larger presence of banks and finance companies relative to direct lenders is reflected in aggregate data as well. We estimate that total deployed capital of direct lenders to U.S. companies as

[13] There are a few 3-digit NAICS codes for firms in the NETS data which are not in the He, Mostrom and Sufi (2024) data set based on Compustat. The nearest available industry is assigned for these industries: 113 and 115 are assigned as 111, 114 is assigned as 112, 487 is assigned as 711, 491 and 493 are assigned as 492, 551 is assigned as 541, and 712 is assigned as 711.

of 2022 is $516B. This reflects $165B from BDCs and $351B from non-BDC direct lending funds.[14] Total commercial and industrial loans for U.S. banks as of 2022 is $2.7 trillion. An important caveat to this discussion is that the shares shown in Table 1 reflect the extensive margin of a lending relationship. The UCC filings do not contain information on the size of the loan. It could be that direct lenders on average provide larger loans than banks and finance companies, which would imply a higher share of total amount of loans outstanding. However, it is interesting to note that the ratio of the share of employment-weighted firms with UCC filings from direct lenders relative to banks (0.08/0.48 = 17%) is similar to the ratio of aggregate direct lending loans outstanding to aggregate bank C&I loans outstanding ($516B/$2700B = 19%).

In terms of collateral, for the private middle market sample, 8% of firms, employment-weighted, have a blanket-lien loan at some point between 2018 to 2022, compared to 23.1% for fixed asset liens and 10% for current asset liens. The collateral code is missing in at least one UCC filing obtained by 38% of the borrowers in the sample. For this same sample, data from PitchBook suggest that 3% of private middle market firms have a PE investment at some point investment from 2018 to 2022 when firms are weighted by employment. The Google Vertex AI measure of PE investments is substantially higher, suggesting that 17% unweighted and 20% employment weighted private middle market firms have a PE investment at some point between 2018 and 2022.

Table 2 presents summary statistics at the lender-level. The sample is limited to lenders that have at least 10 borrowers with a UCC filings between 2018 and 2022. There are 1,344 such lenders, 7% direct lenders, 78% banks, and 15% finance companies. The table also shows the mean of the portfolio characteristics across the lenders in the sample and statistics on the distance between a lender and a borrower. On average, lenders have a median distance to their borrowers of 403 miles.

Comparison with other data on direct lending

In Table A3 in the appendix, we compare the total number of firms in the NETS data set as of 2022 that we are able to match to a UCC filing by a direct lender, an investment by a BDC, and a private credit investment as recorded in PitchBook. As before, these are measured as any investment from 2018 to 2022. Across all three measures, there are a total of 17,431 firms as of 2022 with a

[14] Specifically, BDC Collateral reports $275B total assets for BDCs as of 2022, and Chernenko, Ialenti and Scharfstein (2025) show that BDCs have approximately 60% non-broadly syndicated loan debt, which yields 0.6*$275B = $165B. According to Preqin, for private credit funds other than BDCs, total North American private credit AUM was $1,057B as of 2022, 44% of this is direct lending, and there is $114B of direct lending dry powder, which yields $351B = 0.44*$1057B-$114B.

private credit investment at some point between 2018 and 2022. The coverage by the UCC filings is significantly larger; there are 10,874 firms that are matched to a UCC filing but not matched to either a BDC investment or a private credit investment according to PitchBook. For the private middle market firm sample, the respective numbers are 7,472 total and 4,181 that only have a UCC filing by a direct lender. UCC filings capture a significantly larger share of firms that receive an investment by a direct lender compared to BDC filings or PitchBook.

Table A2 in the appendix shows the fraction of firms with a private credit investment using these alternative three measures across the employment size distribution. UCC filings have substantially more coverage at the smaller end of the size distribution; for example, for firms with between 11 and 20 employees, 0.31% have a UCC filing from a direct lender compared to 0.08% with a BDC investment and 0.04% with a private credit investment measured by PitchBook. The numbers start to even out as employment size increases; for example, for firms between 501 and 1000 employees, 6.1% have a UCC filing with a direct lender, 5.3% have a BDC investment, and 3.0% have a PitchBook-measured private credit investment.

The wider coverage of UCC filings, especially among lower middle market firms, should not be surprising. UCC filings are legal documents that any secured lender must submit to perfect a claim on collateral. As long as a filing is made, it appears in the data, regardless of whether the borrower is publicly visible or the transaction has been covered in the media. This makes UCC filings largely independent of information frictions that may affect data availability in other sources.

The last column of Table A2 in the appendix shows the fraction of all firms that have a private credit investment using the broadest measure possible: whether we find a UCC filing, a BDC investment, or a private credit investment in PitchBook. However, for the analysis below, we continue to use only the UCC filing measure, as it is more comparable to the UCC filings by banks and finance companies, and it better reflects the secured lending positions that are the normal purview of banks and finance companies. See Robinson and Wallskog (2025) for an interesting study on the hybrid security and equity investments by BDCs, which are not the focus of the analysis here.

3 Direct Lenders Focus on a Distinct Set of Borrowers

The firms that borrow from direct lenders are distinct from those that borrow from banks and finance companies, a result shown in this section using the data set of private middle market firms as of 2022. As noted above, a firm is recorded as having an loan from a given type of lender if there is a UCC filing recorded for that firm by the type of lender in question at some point from 2018 and 2022. This strategy allows us to construct the portfolio of borrowers for these three types of lenders: direct lenders, banks, and finance companies.

For these three types of lenders, Figure 1 presents the cumulative distributions of the borrower portfolios for five variables: (1) total employment of the borrower, (2) the age of the borrower, as recorded in NETS, (3) the industry intangibility of the borrower, using the K_{IT}/K_{TOT} ratio from He, Mostrom and Sufi (2024), (4) the credit score of the borrower, according to the PAYDEX score by Dun and Bradstreet, and (5) the population of the city in which the borrower is headquartered.

The distribution of borrower characteristics for banks and finance companies is largely similar across the five variables. This is not the case with direct lenders. The borrowers of direct lenders are larger, younger, more likely to be in intangible capital-intensive industries, and more likely to be located in larger cities. Table 3 shows the mean and distribution of each of these characteristics for direct lenders and for banks and finance companies together. The differences are substantial. The median borrower of a direct lender is 9 years younger than the median borrower of traditional lenders, and is operating in an industry that has a median K_{IT}/K_{TOT} that is 0.105 higher. The median borrower of a direct lender is in a city with 3.7 million people, compared to 2.2 million for the median borrower of a traditional lender. In terms of the PAYDEX credit score, the portfolios of direct lenders and traditional lenders are largely similar.

Panel A of Table 4 highlights the industry differences in the portfolios in more detail. Panel A shows the 10 industries for which direct lender portfolio shares minus traditional lender portfolio shares are the most positive. Direct lenders have a portfolio share in NAICS code 541, Professional, Scientific, and Technical Services, that is 8 percentage points larger. This is among the most intangible capital-intensive industries according to the He, Mostrom and Sufi (2024) measure. Other notable intangible capital-intensive industries for which direct lenders have significantly larger portfolio shares include 513 (Publishing Industries, which includes many software companies), 325 (Chemical Manufacturing, which includes many bio-pharmaceuticals), and high tech manufacturing (334 and 339). On the flip side, traditional lenders have higher portfolio shares in less intangible capital-intensive industries such as 722 (Food services and Drinking Places), 236 (Construction of buildings), and 484 (Truck transportation).

Panel B of Table 4 shows the top 10 cities for which direct lenders have the highest portfolio shares relative to traditional lenders. These 10 cities are among the largest in the country, with New York City, Los Angeles, and Chicago all on the list. Compared to traditional lenders, the borrower portfolios of direct lenders are tilted away from smaller cities and toward larger cities.

Table 5 uses a Mahalanobis distance measure to show formally that the borrower portfolio of direct lenders is distinct from that of banks and finance companies. The Mahalanobis distance measure is similar to a simple Euclidean distance measure, except that it adjusts for the variance-covariance matrix of the characteristics in question. More specifically, the distance measure between the portfolios of lender type i and lender type j is:

$$D_M(\vec{\mu^i}, \vec{\mu^j}) = \sqrt{(\vec{\mu^i} - \vec{\mu^j})^T \Sigma^{-1} (\vec{\mu^i} - \vec{\mu^j})} \tag{1}$$

where $\vec{\mu^i}$ is an n by 4 vector of the means of borrower age, borrower credit score, industry intangibility of the borrower, and population of the city in which the borrower is located for lender type i. The variance-covariance matrix Σ is a 4 by 4 matrix containing the variances and covariances of the four characteristics in question.

For the full sample of middle market firms, the distance between direct lenders and banks and the distance between direct lenders and finance companies is five times larger than the distance between banks and finance companies. Table 5 also displays the distances conditional on different parts of the size distribution. The relative magnitudes are similar, even conditional on size. Across all size categories, the distance between direct lenders and either banks or finance companies is five to seven times larger than the distance between banks and finance companies.

These stark patterns are important because they call in to question the general idea that direct lenders are a substitute for traditional lenders among middle market firms. Direct lenders appear to focus on a unique segment of the market: their borrowers are bigger, younger, more intangible capital-intensive, and more likely to be located in the biggest cities of the country.

4 Primacy of Private Equity

4.1 Private equity and direct lender portfolios

The significant differences between the borrower portfolios of direct lenders and banks are largely due to the fact that direct lenders lend primarily to PE-owned firms. The left panel of Figure 2 shows the fraction of the borrowers in the portfolios of direct lenders, banks, and finance companies that are owned by a PE sponsor. The figure reports this fraction using both the narrow definition of PE ownership, which is whether a firm in NETS can be matched to a PitchBook record of a PE investment, and a broad definition of PE ownership, which is whether the Google Vertex AI strategy finds evidence of ownership between 2018 and 2022.

According to the broad measure, 75% of the borrowers of direct lenders are owned by a PE sponsor. Only 16% and 15% of the borrowers of banks and finance companies, respectively, are owned by a PE sponsor. Using the narrow measure from PitchBook, the fractions are substantially lower across all three groups. However, the qualitative comparison is similar: the borrowers of direct lenders are much more likely to be owned by a PE sponsor compared to the borrowers of banks and finance companies.

Is the same pattern true across all direct lenders, or are there some direct lenders that lend disproportionately to non-PE owned firms? To answer this question, we use the lender-level data set which includes 1,344 lenders that have at least 10 borrowers from 2018 to 2022. This data set allows for the measurement of the share of borrowers in a given lender's borrower portfolio that is owned by a PE sponsor. The right panel of Figure 2 plots the probability mass function of the share of PE-owned borrowers across direct lenders, banks, and finance companies. Almost 85% of the direct lenders in the sample have a portfolio share of PE-sponsored firms that is above 0.60, and 65% are above 0.80. Only one of the direct lenders is below 0.20. In contrast, 72% of banks and 82% of finance companies have a PE-owned share less than 0.20.

Figure 3 formally tests the connection between the results in Section 3 and the patterns shown in Figure 2. This figure plots the coefficient on dl from the following lender-level regression:

$$Y_i = \alpha + \beta * dl_i + \gamma * pe_i + \varepsilon_i \tag{2}$$

where Y_i is a characteristic of the portfolio of lender i, dl_i is an indicator variable for whether lender i is a direct lender, and pe_i is the share of the borrowers in the portfolio of lender i that are owned by a PE sponsor, according to the broader Google Vertex AI measure of PE ownership. In Figure 3, two point estimates for β are shown for each outcome variable Y. The first is from a regression without the pe control included, and then the second comes from a regression with the pe control included. Comparing the two estimates helps answer the question: are borrower portfolio differences between direct lenders and traditional lenders explained by the direct lender concentration on PE-owned firms?

Figure 3 suggests that the answer to this question is "yes." Each outcome variable is scaled by its standard deviation in order to ease interpretation. Consistent with the results already shown in Section 3, there are striking differences across the portfolios of direct lenders and traditional lenders. The portfolios of direct lenders are heavily tilted toward younger, more intangible capital intensive, and large city borrowers. However, these differences largely disappear when the pe control is included.

4.2 Implications for impact of direct lenders across U.S. economy

The focus of direct lenders on PE-owned borrowers implies a particular impact on the overall U.S. economy relative to banks and finance companies. This is due to the fact that private equity tends to invest in specific industries and specific geographical areas, and these proclivities are persistent over time.

For the analysis shown in Figure 4, industries and cities are sorted by the share of companies as of 2007 that are owned by a PE sponsor at some point between 2003 and 2007, as measured by PitchBook. For example, industries that have a large share of PE-owned companies are chemical manufacturing (325), publishing industries (513), and data processing and hosting (518). Cities with a large share of PE-owned companies as of 2007 include Princeton, New Jersey; Salt Lake City, Utah; Denver, Colorado; and Boston, Massachusetts.

The top two panels show a bin-scatter of the 2022 PE share across industries against the 2007 PE share across industries. The top left panel uses PitchBook for the 2022 share, whereas the top right panel uses the Google Vertex AI measure of the 2022 PE share. In both panels, there is a strong positive relationship. The share of PE-owned companies in an industry as of 2007 is strongly related to the share of PE-owned companies in an industry as of 2022. For example, there are four industries in the top six for both 2007 and 2022: chemical manufacturing (325), publishing industries (513), data processing and hosting (518), and management of companies and enterprises (551). A similar pattern emerges when analyzing geography, as shown in the bottom two panels. The share of PE-owned companies in a city as of 2007 is strongly predictive of the PE-owned share as of 2022, using either the PitchBook or Google Vertex AI measure of private equity presence. For example, Boston, Colorado Springs, Denver, and Salt Lake City are all in the top 10 cities in both 2007 and 2022.

It is important to emphasize that the presence of direct lenders in the U.S. economy was limited as of 2007, and so it is unlikely that the 2007 distribution of PE is endogenous to direct lending.

As such, the 2007 distribution of PE can largely be used as an exogenous factor to explain the rise in direct lending. This helps mitigate the concern that the dramatic rise in direct lending may have changed the focus of PE in terms of geography and industries, and allows us to use the PE share as of 2007 across industries and cities as a primitive to help explain the rise in direct lending.

Figure 5 shows that the PE share of an industry (top two panels) or a city (bottom two panels) as of 2007 strongly predicts both the level of direct lending as of 2022 (left two panels) and the rise in direct lending from 2010 to 2022 (right two panels).[15] For example, as the top right panel shows, industries in the top quintile of the distribution of PE share as of 2007 experience a 2 percentage point increase in the share of companies receiving a direct loan from 2010 to 2022. In contrast, industries in the bottom quartile see almost no rise in direct lending from 2010 to 2022.

To explore this pattern further, an industry-city level data set is constructed from the underlying firm-level data. This data set measures the share of companies in a given industry-city cell that receive a direct loan as of 2010 and as of 2022. The rise in the share of companies receiving a direct loan from 2010 to 2022 is then calculated for each industry-city cell.

Table 6 shows the rise in direct lending share from 2010 to 2022 across the 2007 PE industry share and the 2007 PE city share. All averages are weighted by the underlying number of firms in an industry-city cell. Moving from the northwest to the southeast of the table shows how powerful the 2007 PE distribution is in predicting the industry-city rise in direct lending. Industries in the top quintile of the 2007 industry PE share located in cities in the top quintile of the 2007 city PE share (most southeast cell) see a 2 percentage point rise in direct lending. At the other extreme, industries in the bottom quintile of both the city and industry PE share (most northwest cell) see almost no rise in direct lending. Across almost all the rows and columns, the change in direct lending monotonically rises with the 2007 PE share.

Table 7 tests these patterns in a regression framework. Specifically, Table 7 reports estimates from industry-city level regressions:

$$Y_{ic} = \alpha + \beta * pe_{c,2007} + \gamma * pe_{i,2007} + \varepsilon_{ic} \tag{3}$$

where Y_{ic} are measures of outcomes in a city-industry cell, $pe_{c,2007}$ is the PE share of a county as of 2007, and $pe_{i,2007}$ is the PE share of an industry as of 2007. Observations are weighted by the

[15] Recall that the UCC filings are initially available in 2006, and so 2010 is the first year for which a comparable measure to the 2022 can be measured, given that we need five years of data to measure whether a firm has a UCC filing from a direct lender in the last five years.

number of firms in the industry-city cell. Column 1 shows the persistence result: the PE share of a city and an industry as of 2007 strongly predicts the PE share of industry-city as of 2022. Column 2 shows the strong power of PE presence in 2007 in predicting the share of companies with a direct loan as of 2022. For both specifications, the intercept is estimated to be close to zero with a small standard error. In other words, for industry-city cells with no 2007 PE presence, there remains no PE presence and no direct lending presence either.

Column 3 is a key result of the study: the rise in direct lending is significantly larger in industry-city cells that have large PE presence as of 2007. In terms of magnitudes, a one standard deviation increase in the PE share of an industry as of 2007 implies a 0.5 percentage point increase in the direct lender share. Also, the constant is estimated to be zero with a reasonably small standard error: for companies in industries that have low PE share as of 2007 and that are located in cities with low PE share as of 2007, there is no rise in direct lender share from 2010 to 2022. Columns 4 and 5 examine the rise in bank and finance company share across these industry-city cells. The estimates are less precise, but the evidence is less supportive of the view that PE share as of 2007 predicts the rise in the share of companies in an industry-city cell receiving a loan from a bank or finance company.

To provide a few concrete examples, consider the 108 middle market motor vehicle and parts dealers (NAICS code 441) in Kansas City, Missouri as of 2022. The private equity share of this industry and this city as of 2007 are in the lowest respective quintiles of the distributions. As of 2022, none of these 108 companies have a UCC filing from a direct lender. This is despite that fact that 45% have a UCC filing from a bank. On the other extreme, consider the 132 middle market publishing companies (NAICS code 513, which includes software) in Boston, Massachusetts. The private equity share of this industry and this city as of 2007 are in the highest respective quintiles of the distributions. Approximately 6% of these firms have a direct loan as of 2022, and the rise in direct lending from 2010 to 2022 was 4.4%.

Private equity focuses on a particular slice of the U.S. economy, and this slice is where direct lenders have had the largest impact. But outside of these industries and areas, the impact of direct lenders has been minimal.

5 Differences in Lending Technology

The centrality of private equity is an inescapable aspect of direct lending. Why might direct lenders have a comparative advantage in lending to PE-owned borrowers, and why may they be unable or unwilling to lend to non-PE-owned firms in the U.S. economy? This section focuses on the most striking differences in the lending technology between direct lenders and banks to help answer these questions.

5.1 Distance

A well-established result in the banking literature is the importance of geographic proximity in small and medium-size business lending (e.g., Petersen and Rajan (1995), Degryse and Ongena (2005); Mian (2006); Alessandrini, Presbitero and Zazzaro (2009); Agarwal and Hauswald (2010)). The general argument in this literature is that closer geographic proximity gives banks a unique advantage when lending to opaque borrowers, and it may help to overcome issues related to information asymmetry such as adverse selection and moral hazard. A natural question is whether direct lenders are geographically close to their borrowers, given that lending to middle market firms may also face information asymmetry issues. The UCC filings are an excellent source of data that can be used to measure the geographic distance between a borrower and lender, as the filing includes the addresses of both.

Figure 6 shows the median distance between a borrower and their lender, by type of lender. The median distance between a borrower and a direct lender is 1,138 miles. To put this in perspective, this is approximately the driving distance between Chicago and Denver, or between New York City and Orlando. In contrast, the median distance between a bank and a borrower is only 30 miles. Finance companies, in this regard, are more like direct lenders than banks. They too are geographically distant from their borrowers, and the distance is comparable to direct lenders. This is perhaps unsurprising given that the loans provided by finance companies are so directly tied to the collateral. For example, two of the largest finance companies in the data are associated directly with John Deere and Caterpillar.

Banks' proximity to borrowers is a direct function of their expansive branch network. The top left panel of Figure 7 displays a map of the United States with zip codes of direct lender addresses from the UCC filings shaded in blue. Direct lenders are disperse, and they are more likely to be located in major metropolitan areas. The top right panel shows the zip codes of banks from the UCC filings shaded in red. Banks cover almost the entire country. One concern when comparing the top two panels of the figure is that banks have many more UCC filings, which naturally leads to more shaded zip codes. In the bottom left panel, we randomly sample bank UCC filings such that the number of UCC filings by banks are the same as the total number of UCC filings by direct lenders. This helps control for the differences in the relative size of banks and direct lenders. Even fixing the market size of these two intermediaries, banks have a much more disperse presence throughout the country compared to direct lenders.

Direct lenders have a small branch network compared to banks, and this is a likely explanation for why they do not lend widely to non-PE sponsored firms. Without a branch network, direct lenders are more dependent than banks on PE sponsors for sourcing new loans.

5.2 Blanket liens

Another major difference between the lending technology of direct lenders and banks is the use of a so-called "blanket lien." A blanket lien is a security interest by a lender in all of the borrower's assets, as opposed to a security interest in a particular type of collateral such as equipment or property. The idea behind a blanket lien is to ensure that the lender can obtain any value of the assets of the firm in case of default, including the value of the firm if it is to emerge from default as a financially healthy company. Both Lian and Ma (2021) and Caglio, Darst and Kalemli-Özcan (2021) argue that a blanket lien is a claim on the value created by combining the assets of the firm, which may also be referred to as going concern value, as opposed to the liquidation value of separable assets.[16]

The left panel of Figure 8 uses the lender-level data, and it plots the average share of loans that are secured with different types of liens across direct lenders, banks, and finance companies, where the lenders are weighted by the total number of loans they have made. Almost 80% of the loans made by direct lenders are secured with a blanket lien. In contrast, only 15% of loans made by banks are secured with a blanket lien, and only 3% of loans by finance companies are secured with

[16]Lian and Ma (2021): "The collateral value of blanket liens in Chapter 11 is determined by the going-concern cash flow value of the firm (minus the liquidation value of specific assets pledged to asset-based debt)." Caglio, Darst and Kalemli-Özcan (2021): "The common property of accounts receivable and inventory and blanket lien collateral is that their values derive from firm operations, i.e, current fruit. In particular, firm sales combine ideas, intangible capital, marketing of products, etc., which are embedded in the value of the fruit they produce and become capitalized and pledgeable on the balance sheet as AR&I and blanket liens."

a blanket lien. Instead, banks rely more heavily on liens written on fixed assets (e.g., equipment, vehicles) or current assets (e.g., inventory, accounts receivable).

The right panel of Figure 8 plots the probability mass function across the distribution of blanket lien loan share for direct lenders, banks, and finance companies. Almost 75% of the direct lenders have a blanket lien loan share above 0.60, whereas 85% of banks and finance companies have a blanket lien share below 0.20. It is clear that direct lenders, relative to banks and finance companies, have a specialization in blanket liens.

There are a few potential explanations for the higher reliance on blanket liens by direct lenders. PE-owned firms often have much higher leverage ratios relative to non-PE-owned firms, and therefore a higher probability of default. As such, lenders to PE-owned firms have an incentive to ensure the strongest security interest possible to ensure that any residual value of the company in the event of default is acquired by the lender. Consistent with this, Haque, Jang and Mayer (2023b) show that private equity ownership is strongly associated with borrowers' use of loans backed by blanket liens or unsecured debt.

Another explanation is that, compared to banks, direct lenders are better positioned to obtain the going-concern equity value of a company after a default, and a blanket lien facilitates the acquisition of such value. Direct lenders face fewer regulatory restrictions relative to banks in retaining equity ownership of a company; banks are restricted by the Bank Holding Company Act of 1956 from owning or controlling more than 5% of the voting shares of any non-financial company. Similarly, direct lenders may have deeper industry connections in the industry of the borrower, and they may have more patience and ability in finding an acquirer to buy the firm if default materializes. The next section explores whether direct lenders have higher industry specialization relative to banks and finance companies.

In short, the evidence suggests that direct lenders are better positioned than banks to take enterprise value bets on highly leveraged companies, and blanket liens are an important part of this strategy. This argument is also supported by the fact that direct lenders lend more to firms in intangible capital-intensive industries, and so the going-concern value of the company likely exceeds the liquidation value of the separable assets substantially.

5.3 Industry specialization

Excess specialization

A third major difference in the lending strategy of direct lenders relative to banks is a significantly higher degree of industry specialization. In order to measure industry specialization at the lender level, the *excess specialization* measure of Blickle, Parlatore and Saunders (2023) is used. For each lender, excess specialization is defined as how "over-weighted" the lender is in its most over-weighted industry relative to the 'diversified share' that a perfectly diversified lender would invest in that industry. Specifically, the measure is defined as:

$$ExcessSpecialization \equiv \frac{Loans_{l,i}}{\sum_i Loans_{l,i}} - \frac{Loans_i}{\sum_i Loans_i} \tag{4}$$

where $Loans_{l,i}$ is the total number of loans lender l makes in industry i and $Loans_i$ is the total number of loans made in industry i by all lenders. For example, in the UCC data, Antares Capital has the highest loan share in the Professional, Scientific, and Technical Services (NAICS code 541) industry, with a share of 0.18. The share of all loans by all lenders to this industry is 0.11. In this case, Antares Capital has an excess specialization of 0.07.

Table 8 presents lender-level regressions of excess specialization on indicator variables of whether the lender is a direct lender or a finance company. Banks are the omitted group. As column 1 shows, direct lenders have an excess specialization measure that is on average 10 percentage points higher than banks. All estimates in the table come from regressions which also include 20 non-parametric indicator variables for the number of borrowers in a lender's portfolio. These variables are included in the regression to control for the mechanical relationship between the size of the lender's portfolio and its excess specialization in a given industry. Even within narrowly defined size buckets, direct lenders have a higher industry specialization relative to banks.

For robustness, these regressions are also estimated using 2-digit NAICS code industries instead of 3-digit NAICS code industries. Results are also shown from regressions where the definition of excess specialization is varied based on different benchmarks of the bank overall portfolio or the direct lender overall portfolio. The results are broadly consistent. Across the different measures of excess specialization and the different levels of industry aggregation, direct lenders have higher industry specialization than banks.

In fact, finance companies also have a higher industry specialization than banks, and even slightly higher than direct lenders. This should not come as a surprise given that many of the finance companies are captive financing arms of the providers of specific types of equipment that are likely used heavily in certain industries. For example, Caterpillar Financial Services Corporation has a loan share in Heavy and Civil Engineering Construction (NAICS code 237) of 21.1%; the loan share for this industry in the entire sample is only 2.2%.

Direct lender and PE sponsor matches

The excess specialization analysis suggests that industry specialization is an important component of the direct lending business. To further investigate the importance of industry specialization, we examine how PE sponsors and direct lenders "match" in the market place. For this analysis, we utilize information collected from Google Vertex AI on PE sponsors that own firms in the NETS sample. Together with the UCC filings, this allows us to measure whether a given PE sponsor and a given direct lender both have a relationship with the same firm. If a direct lender and a PE sponsor have both invested in the same firm within the last five years, we record this as a "match" between the direct lender and PE sponsor.

For the final data set of potential matches, we limit the sample to PE sponsors and direct lenders that have at least five firms in which they have invested. We then create a balanced panel data set of potential matches where each observation is at the PE sponsor-direct lender level. Every PE sponsor and direct lender pair could potentially match. There are a total of 2,114 PE sponsors and 138 direct lenders, yielding a sample of 291,732 pairs. The critical left hand side variable is whether a given PE sponsor and direct lender experience a match–that is, do they both invest in the same firm at some point between 2018 and 2022. Across the entire set of pairs, there is a 1.1 percentage point likelihood of a match.

We evaluate two potential distance measures to help predict whether a direct lender and PE sponsor match. The first is *geographical distance*, which is the miles between the zip codes of the PE sponsor's and the direct lender's headquarters. The second is a measure of *industry distance*, which reflects how distinct the industry focus of the PE-sponsor is from the industry focus of the direct lender. For this second measure, we use eight industries which both direct lenders and PE sponsors share in their respective top ten industries.[17] We then calculate the share of all deals in

[17] These are NAICS 3-digit codes 541 (Professional, Scientific, and Technical Services), 621 (Ambulatory Health Care Services), 423 (Merchant Wholesalers, Durable Goods), 561 (Administrative and Support Services), 623 (Nursing and Residential Care Facilities), 238 (Specialty Trade Contractors), 424 (Merchant Wholesalers, Nondurable Goods),

these eight industries for every direct lender and every PE sponsor. Finally, we use these shares across the eight industries to calculate the Euclidean distance between industry shares for every PE sponsor-direct lender pair. Importantly, to avoid any mechanical effect of matches on the industry distance measure, this Euclidean distance is calculated excluding any direct match between a given PE sponsor and direct lender. In other words, the industry distance reflects only deals a given PE sponsor and direct lender did with other partners.

The left panel of Figure 9 shows the probability of a match between a direct lender and a PE sponsor across quintiles of industry distance. There is a statistically robust and quantitatively large negative effect of industry distance on the probability of a match. PE sponsor-direct lender pairs that are closest to each other in the industry space have a match probability of 2 percentage points. Those pairs that are furthest from each other in industry space have a match probability of only 0.3 percentage points. The right panel of Figure 9 conducts the same exercise with geographic distance. There is a decline in match probability as the geographic distance between a PE sponsor and a direct lender increases, but it is smaller quantitatively and less precise statistically.

Table 9 presents results from regressions where matches between PE sponsors and direct lenders are related to these distance measures. Given that industry distance and geographical distance are measured in different units, we scale both variables by their standard deviations to ease interpretations. Column 1 shows that a one standard deviation increase in industry distance reduces the probability of a match between a PE sponsor and a direct lender by 0.5 percentage points. The coefficient on physical distance is not statistically distinct from zero at a reasonable confidence level. Column 2 includes both lender and sponsor fixed effects, and the coefficient estimate on industry distance becomes slightly more negative. The constant together with the coefficient estimate on industry distance ease the economic interpretation: a direct lender and a PE sponsor with the exact same industry mix have a 2.4 percentage point likelihood of matching (relative to a sample mean of 1.1 percentage points). A two standard deviation increase in industry distance decreases this probability to 1.2 percentage points. The estimates reported in Columns 3 and 4 are from regressions using the number of deals as a left hand side variable, which allows for an assessment of the intensive margin as well; the results are qualitatively similar.

and 722 (Food Services and Drinking Places).

6 Conclusion and the Future

The stunning rise of direct lending is an exciting development in corporate finance and deserving of more research. However, to paraphrase Mark Twain, the reports of the death of banks in middle market lending are greatly exaggerated. Banks, along with finance companies, remain the largest players in middle market finance in terms of the number of firms that borrow from them. Direct lenders have carved an important niche in the market for lending to PE-owned firms. This specialization implies that direct lenders have made substantial inroads in a particular segment of the overall middle market distribution: younger firms located in larger cities operating within more intangible capital-intensive industries. The lending technology of direct lenders is well-suited for this segment; they are highly specialized by industry and they are more likely to use collateral claims that involve a bet on the continuation value of the firm in case of default.

Going forward, there are a number of questions raised by this study. Will direct lenders ever expand to a large degree beyond PE-sponsored firms? One interesting trend in this direction are recent joint ventures between commercial banks and direct lenders. One such prominent example is Overland Advantage, a joint effort by Centerbridge and Wells Fargo. The press release announcing the the relationship highlights that it "includes differentiated origination sourcing from Wells Fargo's extensive middle market customer base ...", and that the relationship "represents a new paradigm in direct lending, bringing a relationship approach to direct lending and offering a much-needed capital solution in the large but underpenetrated non-sponsor U.S. middle market." This example highlights the difficulty that direct lenders have in sourcing deals outside the PE-sponsor market, and it also points to a potential solution in leveraging banks' clients.

Does the focus of direct lenders on PE-owned companies imply that the growth in private equity is a limit to the growth in direct lending? As of now, the aggregate AUM of private equity is significantly larger than the aggregate AUM of direct lenders; while estimates vary, it is safe to say that PE AUM is at least five times larger than direct lending AUM. In this study, according to the Google Vertex AI measure, there are 80 thousand middle market firms owned by a PE-sponsor at some point between 2018 and 2022. Only 5% of these firms obtained a direct loan during this same period, and so there appears to be plenty of room to grow for direct lenders.

But as the direct lending asset class grows, there is an interesting question of whether the close link to private equity will remain. For example, in recent years, private equity transactions have slowed considerably, which anecdotal evidence suggests has put pressure on direct lenders to invest in alternative asset classes such as broadly syndicated loans and asset-based financing.[18] Of course, providing debt financing in the broadly syndicated loan market to much larger firms, or lending against specific collateral rather than going-concern value, implies a different risk-return profile, which could present a challenge. This is closely related to a broader question: is direct lending more a relationship-based business or can it be transformed into a more arm's length debt market? It is clear that direct lenders rely on PE sponsors to a large degree, but the evidence from the literature suggests that direct lenders also conduct due diligence and monitoring (Jang (2025)). While relationship-based lending may offer more attractive returns, the costs of maintaining such relationships are likely higher. We look forward to research focused on these and related questions.

References

Acharya, Viral V, Nicola Cetorelli, and Bruce Tuckman, "Where do banks end and NBFIs begin?," Technical Report, National Bureau of Economic Research 2024.

Agarwal, Sumit and Robert Hauswald, "Distance and private information in lending," *The Review of Financial Studies*, 2010, *23* (7), 2757–2788.

Albuquerque, Rui A. and Adam Zawadowski, "Private Credit: Risks and Benefits of a Maturity Wall," Working Paper 5189740, SSRN 2025. Last revised: 9 October 2025.

Aldasoro, Iñaki and Sebastian Doerr, "Collateralized lending in private credit," *Available at SSRN 5162211*, 2025.

Alessandrini, Pietro, Andrea F Presbitero, and Alberto Zazzaro, "Banks, distances and firms' financing constraints," *Review of Finance*, 2009, *13* (2), 261–307.

Avalos, Fernando, Sebastian Doerr, and Gabor Pinter, "The global drivers of private credit," *BIS Quarterly Review*, 2025, p. 13.

Axelson, Ulf, Per Strömberg, and Michael S Weisbach, "Why Are Buyouts Levered? The Financial Structure of Private Equity Funds," *The Journal of Finance*, 2009, *64* (4), 1549–1582.

[18] As described in a recent report by Ion Analytics, "private credit funds, awash with record dry powder and starved of deal flow from private equity firms, are now courting listed companies once considered beyond their reach ...". A Bloomberg article also notes that the slowdown in private equity fundraising has prompted an expansion of private credit into providing asset-based financing to smaller businesses.

_ , Tim Jenkinson, Per Strömberg, and Michael S Weisbach, "Borrow cheap, buy high? The determinants of leverage and pricing in buyouts," *The Journal of Finance*, 2013, *68* (6), 2223–2267.

Berger, Allen N and Gregory F Udell, "Relationship lending and lines of credit in small firm finance," *Journal of business*, 1995, pp. 351–381.

_ , Nathan H Miller, Mitchell A Petersen, Raghuram G Rajan, and Jeremy C Stein, "Does function follow organizational form? Evidence from the lending practices of large and small banks," *Journal of Financial economics*, 2005, *76* (2), 237–269.

Bernstein, Shai and Albert Sheen, "The Operational Consequences of Private Equity Buyouts: Evidence from the Restaurant Industry," *Review of Financial Studies*, 2016, *29* (9), 2387–2418.

_ , Josh Lerner, and Filippo Mezzanotti, "Private equity and financial fragility during the crisis," *The Review of Financial Studies*, 2019, *32* (4), 1309–1373.

Blickle, Kristian, Cecilia Parlatore, and Anthony Saunders, "Specialization in banking," Technical Report, National Bureau of Economic Research 2023.

Block, Joern, Young Soo Jang, Steven N Kaplan, and Anna Schulze, "A survey of private debt funds," *The Review of Corporate Finance Studies*, 2024, *13* (2), 335–383.

Boni, Pascal and Sophie Manigart, "Private Debt Fund Returns, Persistence and Market Conditions," *Financial Analysts Journal*, 2023, *78*, 121–144.

Boucly, Quentin, David Sraer, and David Thesmar, "Growth lbos," *Journal of Financial Economics*, 2011, *102* (2), 432–453.

Caglio, Cecilia R, R Matthew Darst, and ebnem Kalemli-Özcan, "Collateral heterogeneity and monetary policy transmission: Evidence from loans to SMEs and large firms," Technical Report, National Bureau of Economic Research 2021.

Cai, Fang and Sharjil Haque, "Private credit: Characteristics and risks," 2024.

Chernenko, Sergey, Isil Erel, and Robert Prilmeier, "Why do firms borrow directly from nonbanks?," *The Review of Financial Studies*, 2022, *35* (11), 4902–4947.

_ , Robert Ialenti, and David S Scharfstein, "Bank capital and the growth of private credit," *Available at SSRN 5097437*, 2025.

Cohn, Jonathan B, Edith S Hotchkiss, and Erin M Towery, "Sources of value creation in private equity buyouts of private firms," *Review of Finance*, 2022, *26* (2), 257–285.

Crane, Leland D. and Ryan A. Decker, "Research with Private Sector Business Microdata: The Case of NETSD&B," Conference Paper / Working Paper (NBER), National Bureau of Economic Research 2020. NBER Conference Paper, July 12, 2020.

Davis, Steven J., John C. Haltiwanger, Kyle Handley, Josh Lerner, Ben Lipsius, and Javier Miranda, "The (Heterogeneous) Economic Effects of Private Equity Buyouts," *Management Science*, 2021, *67* (4), 1904–1923.

Davis, Steven J, John Haltiwanger, Kyle Handley, Ron Jarmin, Josh Lerner, and Javier Miranda, "Private equity, jobs, and productivity," *American Economic Review*, 2014, *104* (12), 3956–3990.

Davydiuk, Tetiana, Isil Erel, Wei Jiang, and Tatyana Marchuk, "Common Investors Across the Capital Structure: Private Debt Funds as Dual Holders," *Fisher College of Business WP*, 2024, (2024-21).

_ , Tatyana Marchuk, and Samuel Rosen, "Direct lenders in the US middle market," *Journal of Financial Economics*, 2024, *162*, 103946.

_ , _ , and _ , "Market discipline in the direct lending space," *The Review of Financial Studies*, 2024, *37* (4), 1190–1264.

Degryse, Hans and Steven Ongena, "Distance, lending relationships, and competition," *The Journal of Finance*, 2005, *60* (1), 231–266.

Demiroglu, Cem and Christopher M James, "The role of private equity group reputation in LBO financing," *Journal of Financial Economics*, 2010, *96* (2), 306–330.

Diamond, Douglas, "Financial intermediation and delegated monitoring," *The review of Economic Studies*, 1984, *51* (3), 393–414.

Diamond, Douglas W and Raghuram G Rajan, "Liquidity risk, liquidity creation, and financial fragility: A theory of banking," *Journal of political Economy*, 2001, *109* (2), 287–327.

Eaton, Charlie, Sabrina T Howell, and Constantine Yannelis, "When investor incentives and consumer interests diverge: Private equity in higher education," *The Review of Financial Studies*, 2020, *33* (9), 4024–4060.

Ellias, Jared A. and Elisabeth de Fontenay, "The Credit Markets Go Dark," *Yale Law Journal*, 2025, *134* (1).

Erel, Isil, Thomas Flanagan, and Michael S Weisbach, "Risk-adjusting the returns to private debt funds," Technical Report, National Bureau of Economic Research 2024.

Fracassi, Cesare, Alessandro Previtero, and Albert Sheen, "Barbarians at the store? Private equity, products, and consumers," *The Journal of Finance*, 2022, *77* (3), 1439–1488.

Fritsch, Laura, Wayne Lim, Alexander Montag, and Martin C. Schmalz, "Direct Lending: Evidence from European and US Markets," *The Journal of Alternative Investments*, 2022, *24* (3), 80–98.

Gompers, Paul, Steven N. Kaplan, and Vladimir Mukharlyamov, "What do private equity firms say they do?," *Journal of Financial Economics*, 2016, *121* (3), 449–476.

Gonzales-Uribe, Juanita and Cynthia Mei Balloch, "Leverage limits in good and bad times," *Working Paper*, 2021.

Gopal, Manasa and Philipp Schnabl, "The rise of finance companies and fintech lenders in small business lending," *The Review of Financial Studies*, 2022, *35* (11), 4859–4901.

Gornall, Will, Oleg R. Gredil, Sabrina T. Howell, Xing Liu, and Jason Sockin, "Do Employees Cheer for Private Equity? The Heterogeneous Effects of Buyouts on Job Quality," *Management Science*, 2025, *71* (5), 4287–4317.

Gupta, Atul, Sabrina T. Howell, Constantine Yannelis, and Abhinav Gupta, "Does Private Equity Investment in Healthcare Benefit Patients? Evidence from Nursing Homes," *Management Science*, 2021, *67* (11), 7021–7043.

Haque, Sharjil, "Does Private Equity Over-Lever Portfolio Companies?," *Available at SSRN 3898848*, 2022.

_ and Anya Kleymenova, "Private Equity and Corporate Borrowing Constraints: Evidence from Loan Level Data," *Available at SSRN 4361582*, 2023.

_ , Simon Mayer, and Irina Stefanescu, "Private Debt versus Bank Debt in Corporate Borrowing," 2025.

_ , _ , and Teng Wang, "How Private Equity Fuels Non-Bank Lending," *Available at SSRN 4429521*, 2023.

_ , Young Soo Jang, and Jessie Jiaxu Wang, "Indirect Credit Supply: How Bank Lending to Private Credit Shapes Monetary Policy Transmission," *Available at SSRN 5125733*, 2025.

_ , _ , and Simon Mayer, "Private Equity and Corporate Borrowing Constraints: Evidence from Loan Level Data," *Available at SSRN 4294228*, 2023.

He, Bianca, Lauren I. Mostrom, and Amir Sufi, "Investing in Customer Capital," 2024.

Hotchkiss, Edith S, David C Smith, and Per Strömberg, "Private equity and the resolution of financial distress," *The Review of Corporate Finance Studies*, 2021, *10* (4), 694–747.

Ivashina, Victoria, "Asymmetric Information Effects on Loan Spreads," *Journal of Financial Economics*, 2009, *92* (2), 300–319.

_ , "The Role of Private Debt in the Financial Ecosystem," Technical Report Working Paper No. 34426, National Bureau of Economic Research 2025.

_ **and Anna Kovner**, "The private equity advantage: Leveraged buyout firms and relationship banking," *The Review of Financial Studies*, 2011, *24* (7), 2462–2498.

Jang, Young Soo, "Are Direct Lenders More Like Banks or Arm's-Length Investors?," *Working Paper*, 2025.

_ **and Ginha Kim**, "Valuation Discipline in Private Credit," *Working Paper*, 2025.

_ **, Dasol Kim, and Amir Sufi**, "Private Credit at Scale: Evidence from US Regulatory Data," *Working Paper*, 2025.

Kaplan, Steven and Jeremy Stein, "The Evolution of Buyout Pricing and Financial Structure in the 1980s," *Quarterly Journal of Economics*, 1993, *108* (2), 313–357.

Kaplan, Steven N and Per Stromberg, "Leveraged buyouts and private equity," *Journal of economic perspectives*, 2009, *23* (1), 121–46.

Kashyap, Anil, Raghuram Rajan, and Jeremy Stein, "Banks as Liquidity Providers: An Explanation for the Coexistence of Lending and Deposit-taking," *Journal of Finance*, 2002, *57*, 33–73.

Lerner, Josh, Morten Sorensen, and Per Strömberg, "Private equity and long-run investment: The case of innovation," *The Journal of Finance*, 2011, *66* (2), 445–477.

Levin, John and Antoine Malfroy-Camine, "Bank Lending to Private Equity and Private Credit Funds: Insights from Regulatory Data," *FRB of Boston Supervisory Research & Analysis Unit Notes*, 2025, (2025-02).

Lian, Chen and Yueran Ma, "Anatomy of corporate borrowing constraints," *The Quarterly Journal of Economics*, 2021, *136* (1), 229–291.

Loumioti, Maria, "Direct lending: The determinants, characteristics and performance of direct loans," *Characteristics and Performance of Direct Loans (May 30, 2022)*, 2022.

Malenko, Andrey and Nadya Malenko, "A theory of LBO activity based on repeated debt-equity conflic," *Journal of Financial Economics*, 2015, *117* (3), 607–627.

Mian, Atif, “Distance constraints: The limits of foreign lending in poor economies,” *The Journal of Finance*, 2006, *61* (3), 1465–1505.

Mittal, Vrinda, “Desperate Capital Breeds Productivity Loss: Evidence from Public Pension Investments in Private Equity,” SSRN Working Paper 2025.

Munday, S., W. Hu, and J. Zhang, “Performance of private credit funds: A first look,” *Journal of Alternative Investments*, 2018, *21*, 31–51.

Neumark, David, Brandon Wall, and Junfu Zhang, “Do Small Businesses Create More Jobs? New Evidence for the United States from the National Establishment Time Series,” *Review of Economics and Statistics*, 2011, *93* (1), 16–29.

Petersen, Mitchell A. and Raghuram G. Rajan, “The Effect of Credit Market Competition on Lending Relationships,” *The Quarterly Journal of Economics*, 1995, *110* (2), 407–443.

Rintamäki, Paul and Sascha Steffen, “PIK Now and Pay Later – How Deferred Interest Reshapes Private Credit,” *Available at SSRN 5341145*, 2025.

Robinson, David T and Melanie Wallskog, “Why is Private Lending So Popular?,” *Available at SSRN 5433596*, 2025.

Shive, Sophie and Margaret Forster, “Sponsor reputation and capital structure dynamics in leveraged buyouts,” *Working Paper*, 2023.

Sufi, Amir, “Information Asymmetry and Financing Arrangements: Evidence from Syndicated Loans,” *Journal of Finance*, 2007, *62* (2), 629–668.

Suhonen, Antti, “Direct Lending Returns,” *Financial Analysts Journal*, 2024, *80*, 1069–1097.

Table 1: Summary Statistics, Firm-level Data Set

	Full Sample			*Private Middle Market*		
	N	Unweighted Mean	Employment-weighted Mean	N	Unweighted Mean	Employment-weighted Mean
Panel A: Firm Characteristics						
Employment	7,656,019	14.2	99255.1	466,669	66.1	196.6
Age	7,608,566	16.0	54.4	459,332	34.1	39.0
Credit Score (PAYDEX)	2,944,526	69.4	72.5	350,373	68.5	68.6
Industry K_{IT}/K_{TOT}	7,656,019	0.479	0.446	466,669	0.458	0.462
City Population, Millions	7,251,346	4.6	4.9	441,443	4.4	4.5
Public Company	7,656,019	0.001	0.188	466,669	0.000	0.000
Panel B: Lender Types						
Loan (Any)	7,656,019	0.124	0.504	466,669	0.380	0.462
Direct Lenders	7,656,019	0.002	0.078	466,669	0.012	0.025
Banks	7,656,019	0.105	0.475	466,669	0.338	0.413
Finance Companies	7,656,019	0.042	0.352	466,669	0.138	0.193
Private Credit (Broad)	7,656,019	0.002	0.120	466,669	0.016	0.035
Panel C: Collateral Type						
Blanket Liens	7,656,019	0.010	0.227	466,669	0.046	0.082
Fixed Assets	7,656,019	0.056	0.374	466,669	0.173	0.231
Current Assets	7,656,019	0.022	0.235	466,669	0.076	0.097
Other Assets	7,656,019	0.003	0.136	466,669	0.012	0.021
Missing Collateral	7,656,019	0.089	0.455	466,669	0.302	0.377
Panel D: Private Equity Owned						
PE-owned (PitchBook)	7,656,019	0.002	0.053	466,669	0.015	0.028
PE-owned (Gemini)				466,669	0.172	0.195

The data are as of 2022, and the variables for loans and private equity reflect whether the firm obtained the variable in question at some point between 2018 and 2022.

Table 2: Summary Statistics, Lender-Level Data Set

	N	Unweighted Mean	# Borrowers-weighted Mean
Panel A: Lender Characteristics			
Number of Borrowers	1,344	242.3	3768.9
Direct Lenders	1,344	0.073	0.015
Banks	1,344	0.775	0.707
Finance Companies	1,344	0.152	0.278
Panel B: Median Borrower Characteristics			
Employment	1,344	48.6	49.6
Age	1,344	33.3	33.6
Credit Score (PAYDEX)	1,344	72.9	73.0
Industry K_{IT}/K_{TOT}	1,344	0.5	0.5
City Population, Millions	1,344	2.7	2.7
Panel C: Geographic Distance			
Median Distance to Borrowers (Miles)	1,343	403	777
Panel D: Private Equity Owned			
PE-owned (PitchBook)	1,344	0.034	0.030
PE-owned (Gemini)	1,344	0.188	0.178
Panel E: Collateral Type (Share of Loans)			
Blanket Liens	1,312	0.132	0.128
Fixed Assets	1,312	0.589	0.641
Current Assets	1,312	0.242	0.202
Other Assets	1,312	0.037	0.029

The data are as of 2022, and reflect the portfolio of borrowers for each lender from 2018 to 2022. The data are for private middle market borrowers.

Table 3: Borrower Characteristics, by Lender Type

	Mean	p10	p25	Median	p75	p90
Panel A: Employment						
Direct Lenders	135.9	26.0	37.0	68.0	150.0	346.0
Banks and Finance Companies	80.2	23.0	28.0	42.0	78.0	165.0
Panel B: Age						
Direct Lenders	30.4	8.0	14.0	24.0	40.0	60.0
Banks and Finance Companies	37.9	11.0	19.0	33.0	50.0	72.0
Panel C: Industry K_{IT}/K_{TOT}						
Direct Lenders	0.578	0.175	0.363	0.662	0.816	0.816
Banks and Finance Companies	0.481	0.159	0.246	0.557	0.667	0.816
Panel D: Credit Score (PAYDEX)						
Direct Lenders	68.2	51.0	63.0	72.0	78.0	80.0
Banks and Finance Companies	69.2	53.0	65.0	73.0	79.0	80.0
Panel E: City Population, Millions						
Direct Lenders	5.61	0.37	1.18	3.70	7.40	12.91
Banks and Finance Companies	4.27	0.13	0.46	2.21	6.25	12.91

Table 4: Borrower Portfolio Differences: Direct Lenders vs. Banks/Finance Companies

Panel A: Industry Distribution

Industries with Higher Direct Lender Portfolio Share

NAICS-3	Industry	Direct Lender	Bank/FC	Difference	Industry K_{IT}/K_{TOT}
541	Professional Svcs	0.198	0.119	0.079	0.816
623	Nursing Facilities	0.048	0.022	0.026	0.064
513	Publishing Industries	0.026	0.006	0.020	0.893
551	Mgmt of Companies	0.021	0.006	0.015	0.816
561	Admin & Support Svcs	0.064	0.049	0.015	0.743
621	HealthCare Svcs	0.073	0.059	0.014	0.667
423	Durable Goods Whslrs	0.070	0.057	0.013	0.662
325	Chemical Mfg	0.020	0.009	0.011	0.871
334	Computer & Electronic Mfg	0.021	0.009	0.011	0.793
339	Medical Equip Mfg	0.020	0.009	0.010	0.804

Industries with Higher Bank/FC Portfolio Share

NAICS-3	Industry	Direct Lender	Bank/FC	Difference	Industry K_{IT}/K_{TOT}
238	Specialty Trade Contractors	0.038	0.082	-0.044	0.574
441	Motor Vehicle Retail	0.007	0.051	-0.043	0.315
722	Food Svcs & Drink Places	0.027	0.058	-0.030	0.222
236	Constr of Buildings	0.007	0.030	-0.023	0.175
237	Heavy & Civil Eng Constr	0.009	0.023	-0.014	0.281
484	Truck Transp	0.007	0.019	-0.013	0.050
624	Social Assistance	0.009	0.022	-0.013	0.246
721	Accommodation	0.008	0.019	-0.010	0.159
713	Amusement & Recreation	0.011	0.021	-0.010	0.273
445	Food & Bev Retail	0.008	0.016	-0.008	0.126

Panel B: Geographic Distribution (City)

Metro Areas with Higher Direct Lender Portfolio Share

Metro Area	Direct Lender	Bank/FC	Difference	City Population, Millions
New York-Newark-Jersey City, NY-NJ	0.092	0.069	0.023	19.62
Los Angeles-Long Beach-Anaheim, CA	0.067	0.044	0.023	12.91
Boston-Cambridge-Newton, MA-NH	0.037	0.020	0.016	4.93
Dallas-Fort Worth-Arlington, TX	0.039	0.025	0.015	7.97
San Francisco-Oakland-Fremont, CA	0.029	0.016	0.013	4.60
Atlanta-Sandy Springs-Roswell, GA	0.030	0.017	0.013	6.25
Chicago-Naperville-Elgin, IL-IN	0.052	0.039	0.013	9.31
Denver-Aurora-Centennial, CO	0.018	0.009	0.008	2.99
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	0.030	0.022	0.008	6.25
San Jose-Sunnyvale-Santa Clara, CA	0.013	0.006	0.007	1.95

Table 5: Mahalanobis Distances of Borrower Portfolio, by Employment Size Category

	Employment					
	All	21-50	51-100	101-200	201-500	501-1000
Direct Lender-Bank Distance	0.800	0.670	0.584	0.509	0.494	0.482
Direct Lender - FC Distance	0.785	0.744	0.665	0.551	0.519	0.547
Bank - FC Distance	0.164	0.141	0.113	0.070	0.087	0.110

Table 6: Mean Change in Direct Lender Share 2010-2022, by 2007 PE Share Quintiles

	PE Share of City, 2007				
PE Share of Industry, 2007	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Quintile 1	0.002	0.002	0.004	0.005	0.005
Quintile 2	0.004	0.006	0.008	0.007	0.010
Quintile 3	0.003	0.005	0.008	0.008	0.009
Quintile 4	0.005	0.013	0.016	0.014	0.019
Quintile 5	0.009	0.014	0.017	0.020	0.020

Each cell reflects the change in the share of firms in the cell that receive a direct loan from 2010 to 2022. Industries are sorted by the 2007 share of firms with PE ownership (rows) and cities are sorted by the 2007 share of firms with PE ownership (columns).

Table 7: Predicting Rise of Direct Lenders at Industry-City Level

	(1) PE Share 2022	(2) DL Share 2022	(3) Δ DL Share 10–22	(4) Δ Bank Share 10–22	(5) Δ FC Share 10–22
PE Share of City, 2007	1.807**	1.809**	1.301**	-0.730	-3.353**
	(0.480)	(0.351)	(0.264)	(1.115)	(1.138)
PE Share of Industry, 2007	2.756**	1.833**	1.313**	1.434	-0.099
	(0.361)	(0.246)	(0.216)	(0.952)	(0.852)
Constant	-0.001	-0.001	-0.001	0.040**	-0.002
	(0.002)	(0.001)	(0.001)	(0.008)	(0.008)
Observations	16,776	16,776	16,776	16,776	16,776
R-squared	0.165	0.115	0.052	0.002	0.004

All regressions are weighted by the number of firms as of 2007 in the industry-city cell. Standard errors are double-clustered by industry and city.

Table 8: Direct Lenders and Industry Specialization

	3-digit Industry Level			2-digit Industry Level		
	(1)	(2)	(3)	(4)	(5)	(6)
	Specialization			Specialization		
Direct Lender	0.101**	0.100**	0.071**	0.108**	0.106**	0.059**
	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
Finance Company	0.124**	0.125**	0.117**	0.155**	0.156**	0.136**
	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)
Observations	1,749	1,749	1,749	1,749	1,749	1,749
R-squared	0.647	0.646	0.628	0.606	0.605	0.557
Benchmark	All	Bank	DL	All	Bank	DL
Industry level	3-digit	3-digit	3-digit	2-digit	2-digit	2-digit

All regressions include size category dummies (not reported). Benchmark indicates which lender group is set as the reference category for calculating industry specialization. Heteroskedasticity-robust standard errors are reported.

Table 9: Lender–Sponsor Distance and Deal Activity

	(1) Deal (0/1)	(2) Deal (0/1)	(3) asinh (# Deals)	(4) asinh (# Deals)
Industry distance	-0.521**	-0.580**	-0.605**	-0.656**
	(0.001)	(0.001)	(0.001)	(0.001)
Physical distance	-0.134	-0.165**	-0.184*	-0.211**
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	2.266**	2.418**	2.630**	2.762**
	(0.003)	(0.003)	(0.004)	(0.003)
Observations	291,732	291,732	291,732	291,732
R-squared	0.003	0.060	0.002	0.062
Lender FE	No	Yes	No	Yes
Sponsor FE	No	Yes	No	Yes

The dependent variable is either a binary indicator for having at least one deal (*Deal (0/1)*) or the inverse hyperbolic sine of the number of deals (*asinh(# Deals)*), which provides a log-like transformation that retains zero values. Independent variables are standardized by dividing each variable by its standard deviation. Coefficients are multiplied by 100 to express effects in percentage points. Standard errors are clustered at the lender and sponsor levels.

Figure 1: Borrower Portfolio Distributions by Lender Type

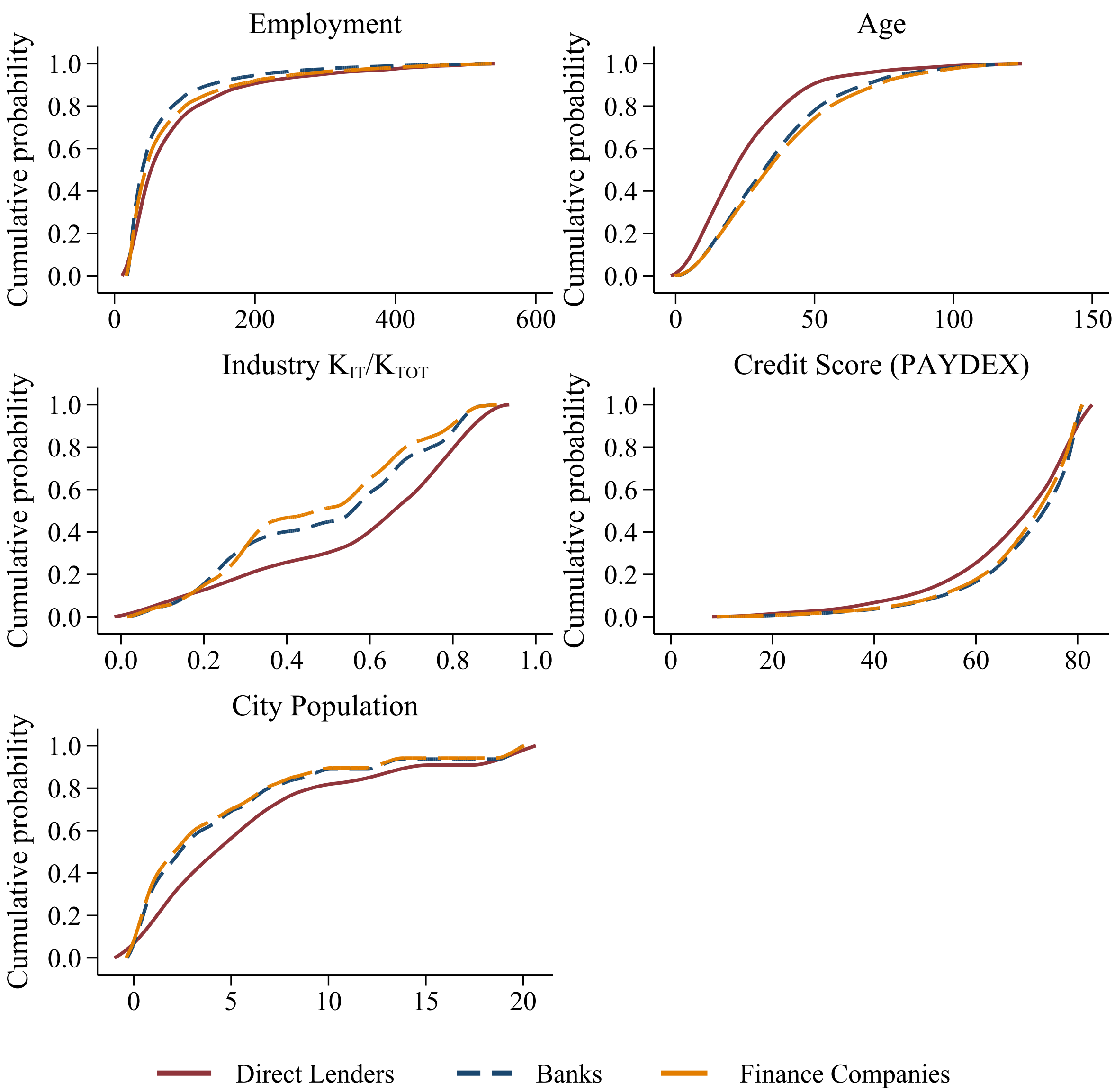


Figure 2: PE Share of Borrowers, by Lender Type

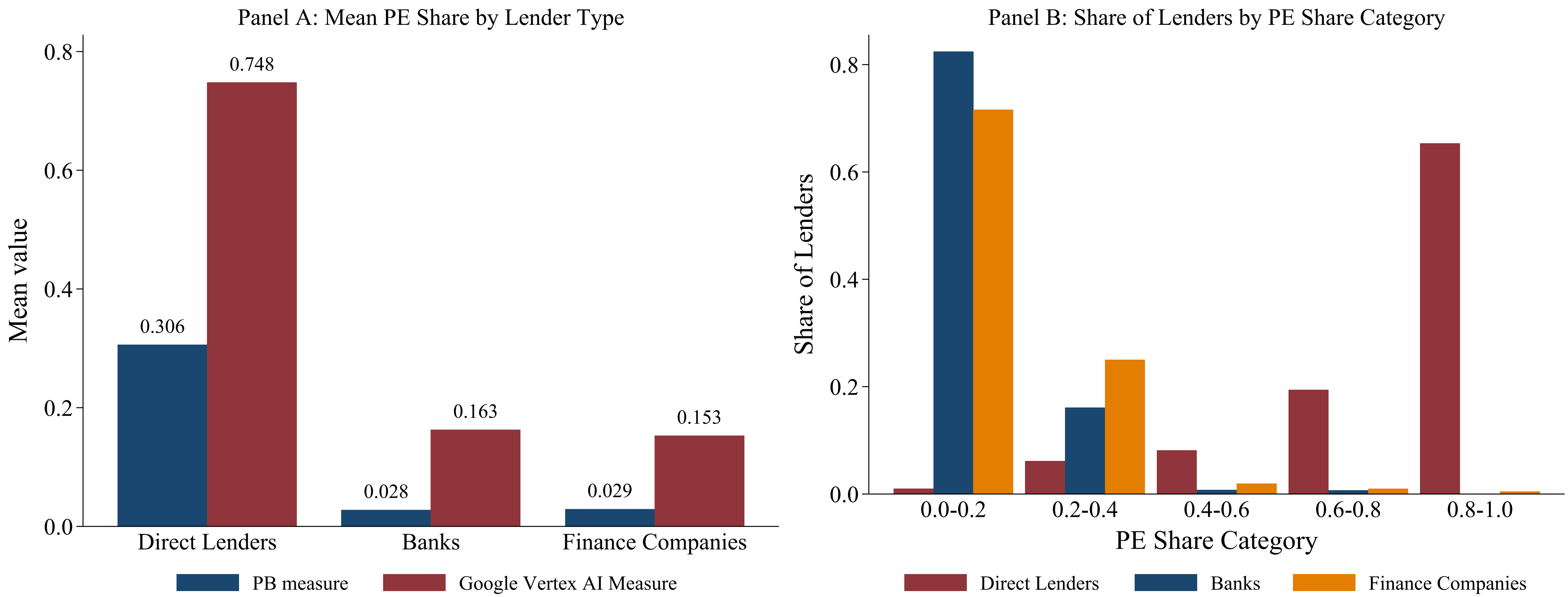
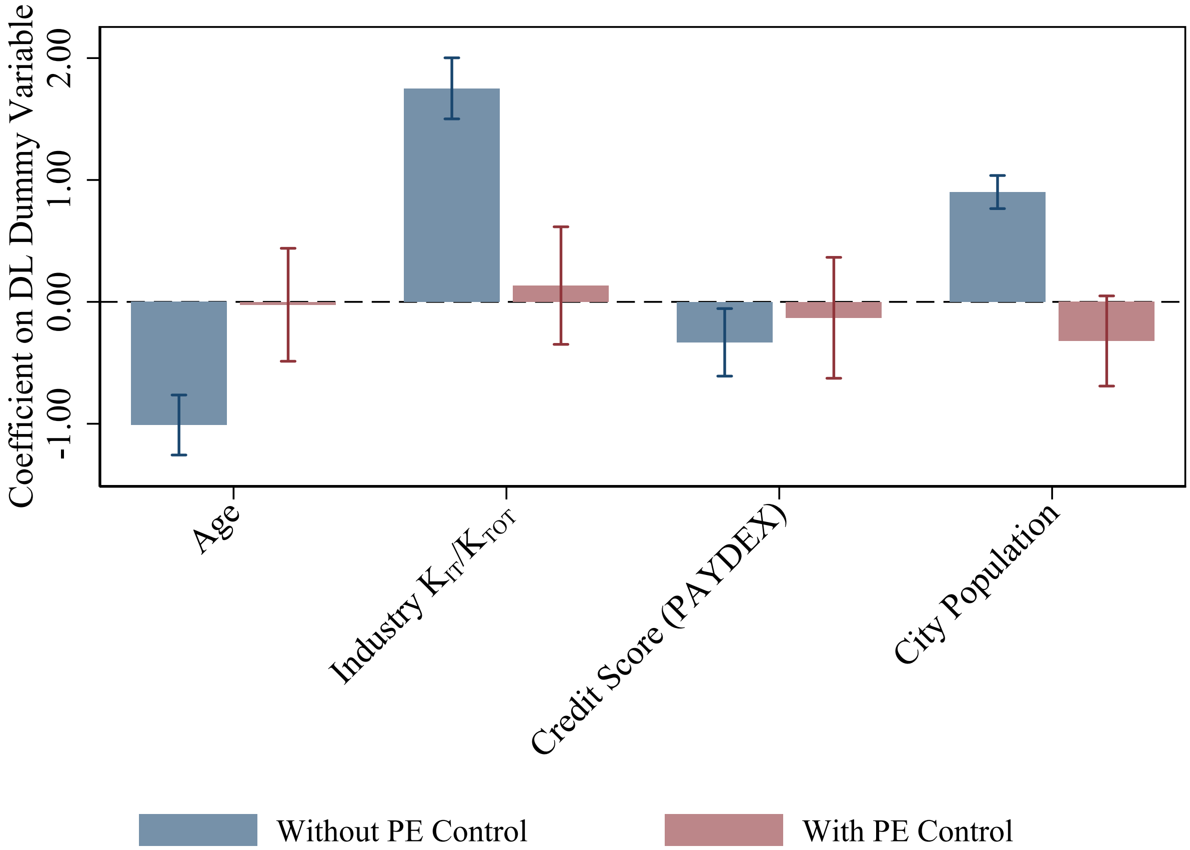
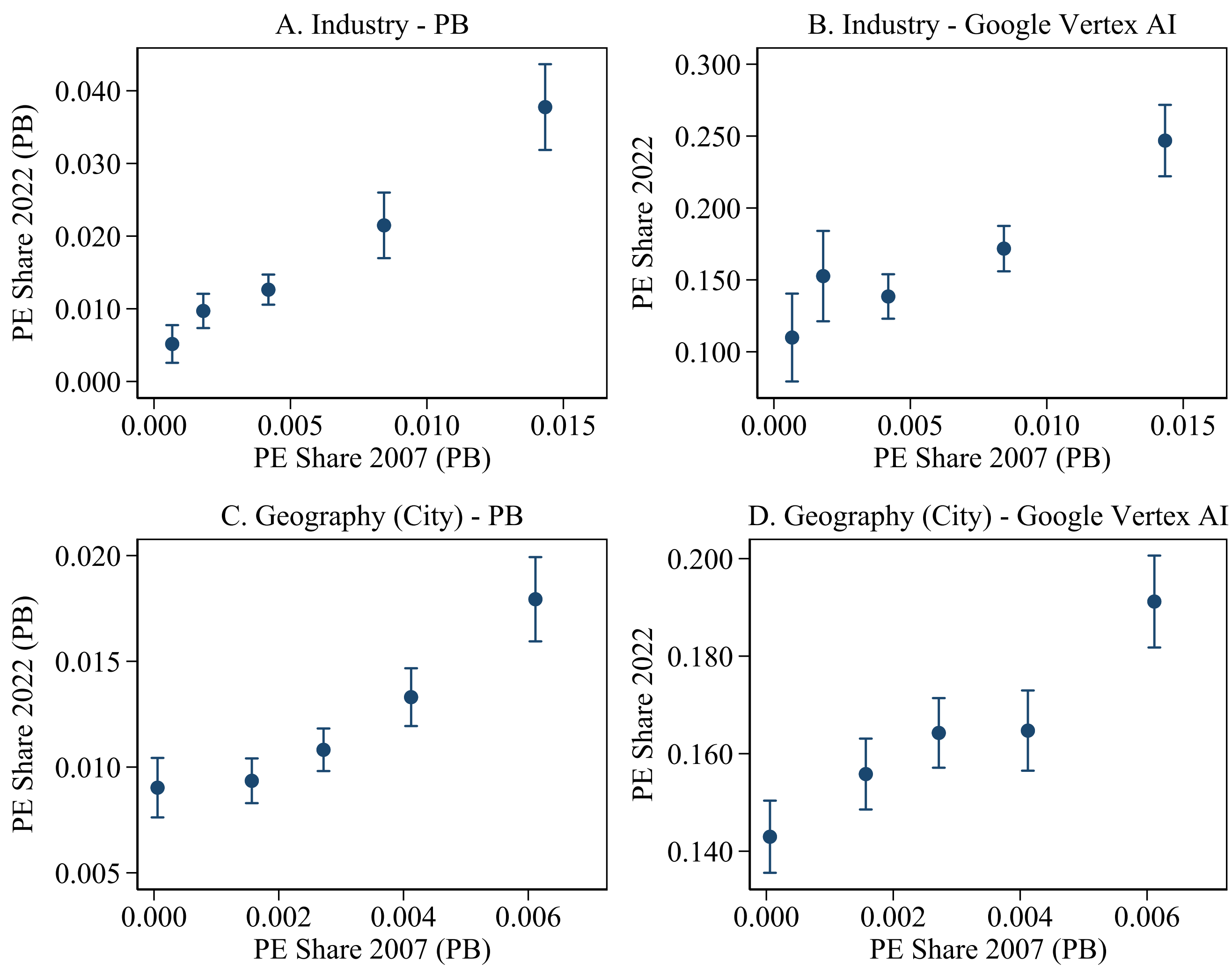


Figure 3: Differences in Borrower Portfolio Characteristics for Direct Lenders



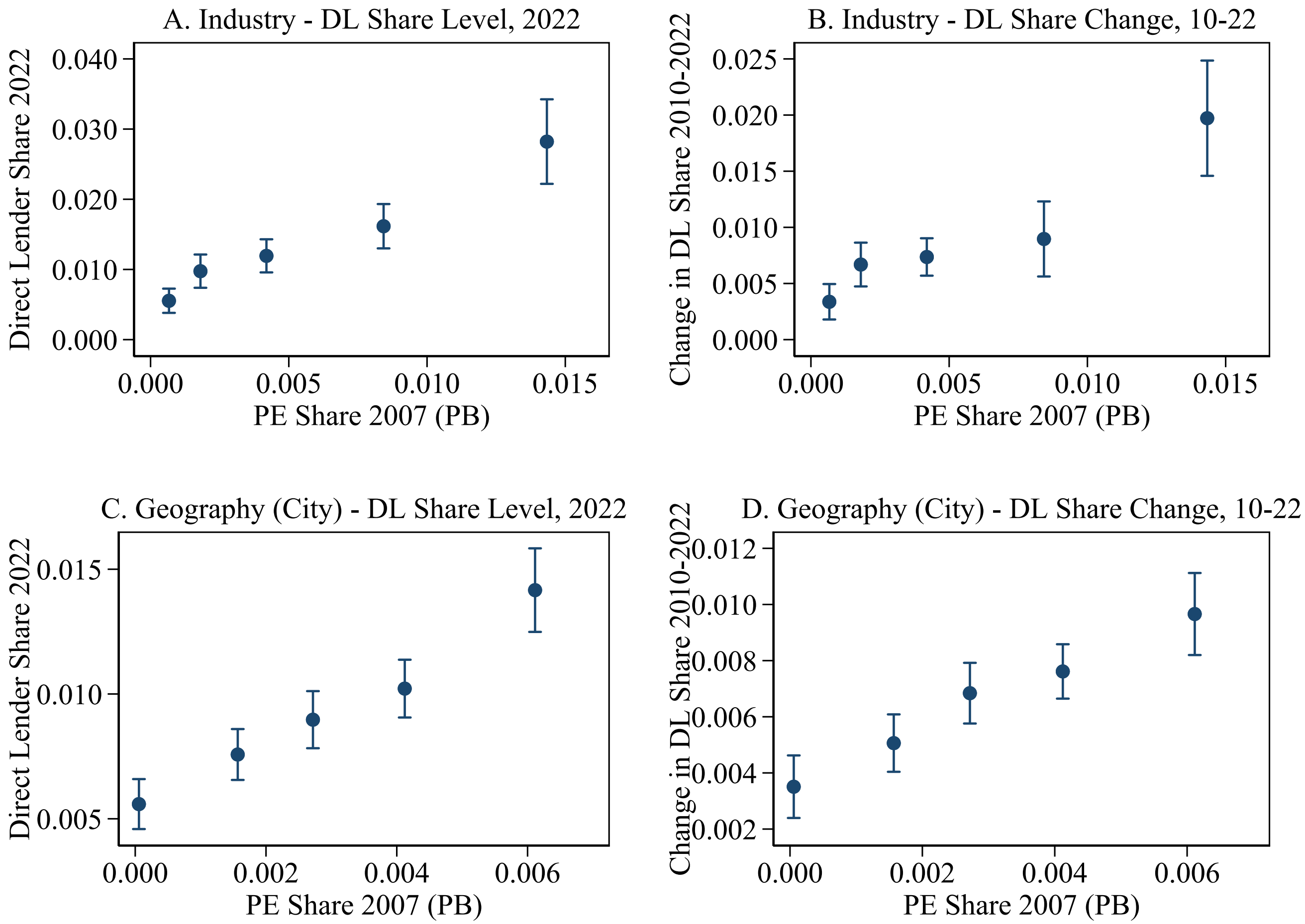
This figure reports coefficients on the direct lender indicator variable from a lender-level regression. The blue bars are for a specification without a control for the share of PE-owned firms in the lender portfolio, and the red bars are for a specification with the control.

Figure 4: PE Persistence by Industry and Geography



This figure shows a bin scatter of industries (top two panels) and cities(bottom two panels). The share of firms in a given industry/city as of 2022 owned by a PE sponsor is related to the share of firms in a given industry/city as of 2007 owned by a PE sponsor.

Figure 5: Predicting Rise in Direct Lending



This figure shows a bin scatter of industries (top two panels) and cities(bottom two panels). The share of firms in a given industry/city as of 2022 with a direct loan and the change in teh share from 2010 to 2022 is related to the share of firms in a given industry/city as of 2007 owned by a PE sponsor.

Figure 6: Median Distance to Borrowers

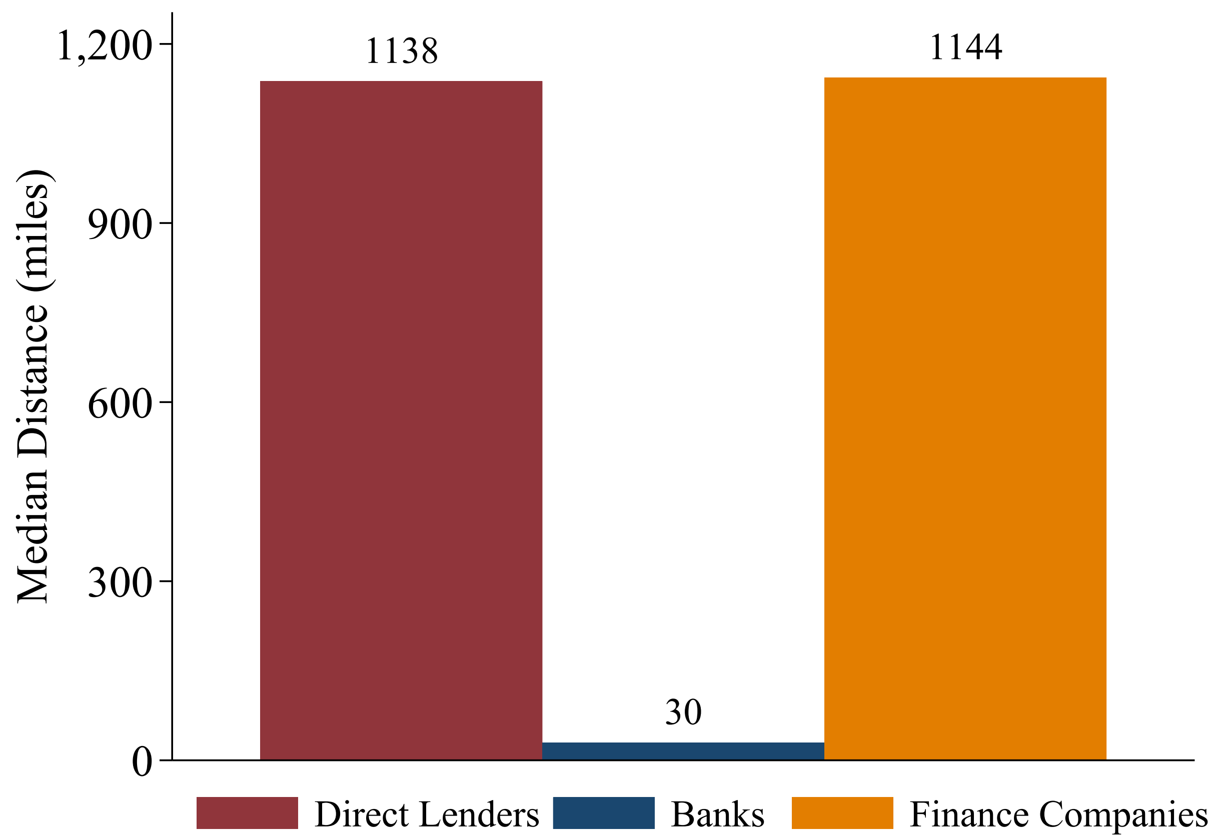
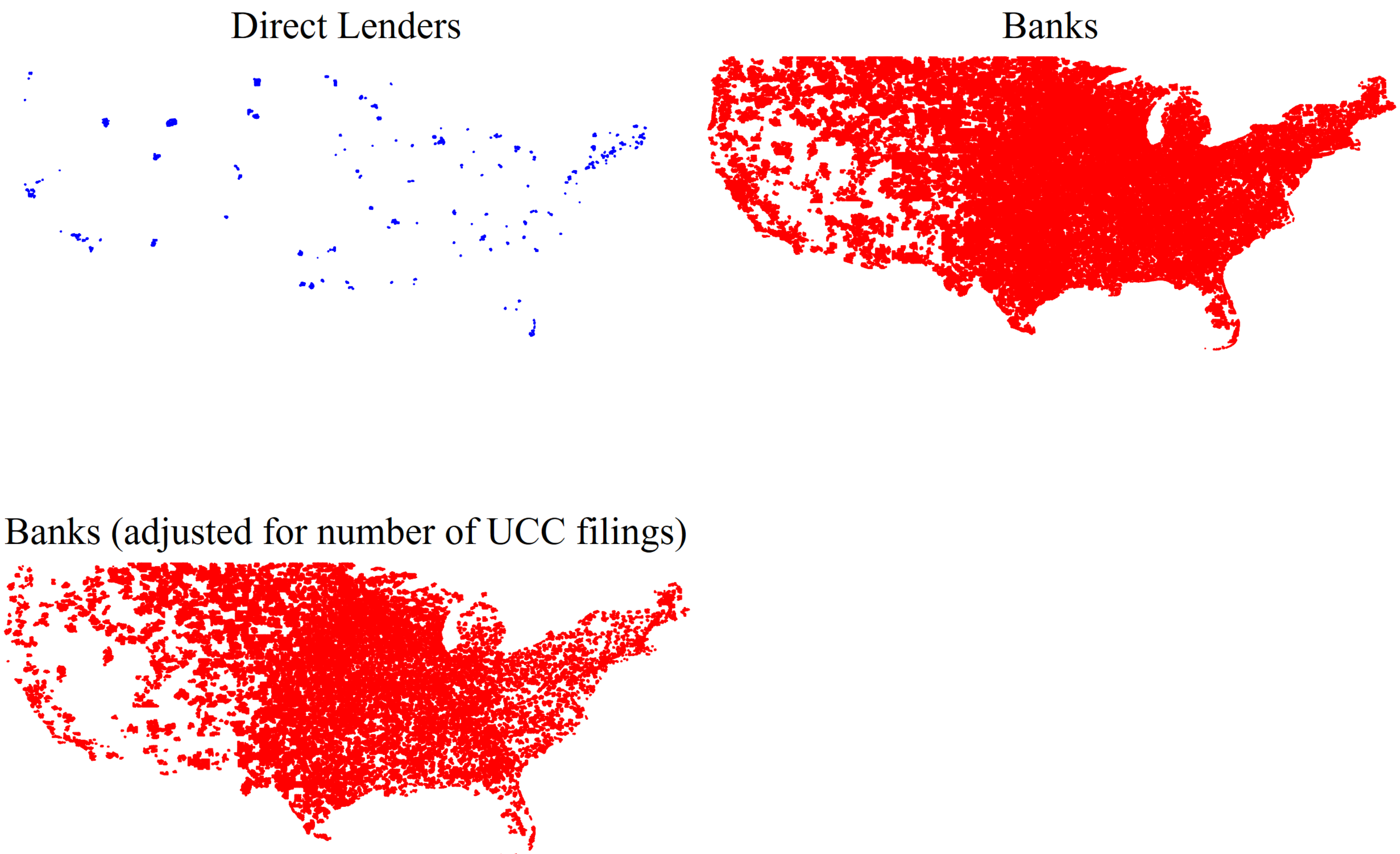


Figure 7: Lender Branch Network Across the United States



The top two panels show the zip codes in which a direct lender or bank lender is located. The bottom-left panel randomly samples bank UCC filings such that the total number of filings are the same for banks and direct lenders, meaning the number of UCC filings is the same in the two left panels.

Figure 8: Blanket Lien Usage, by Lender Type

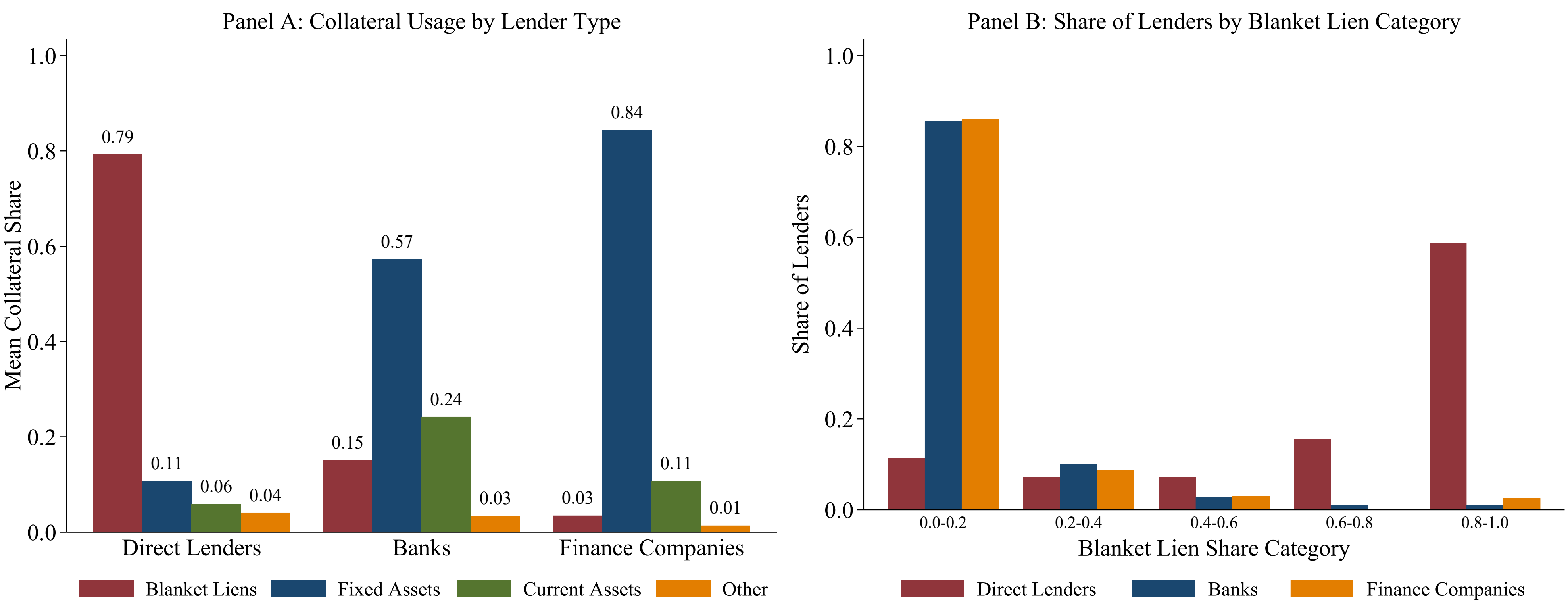
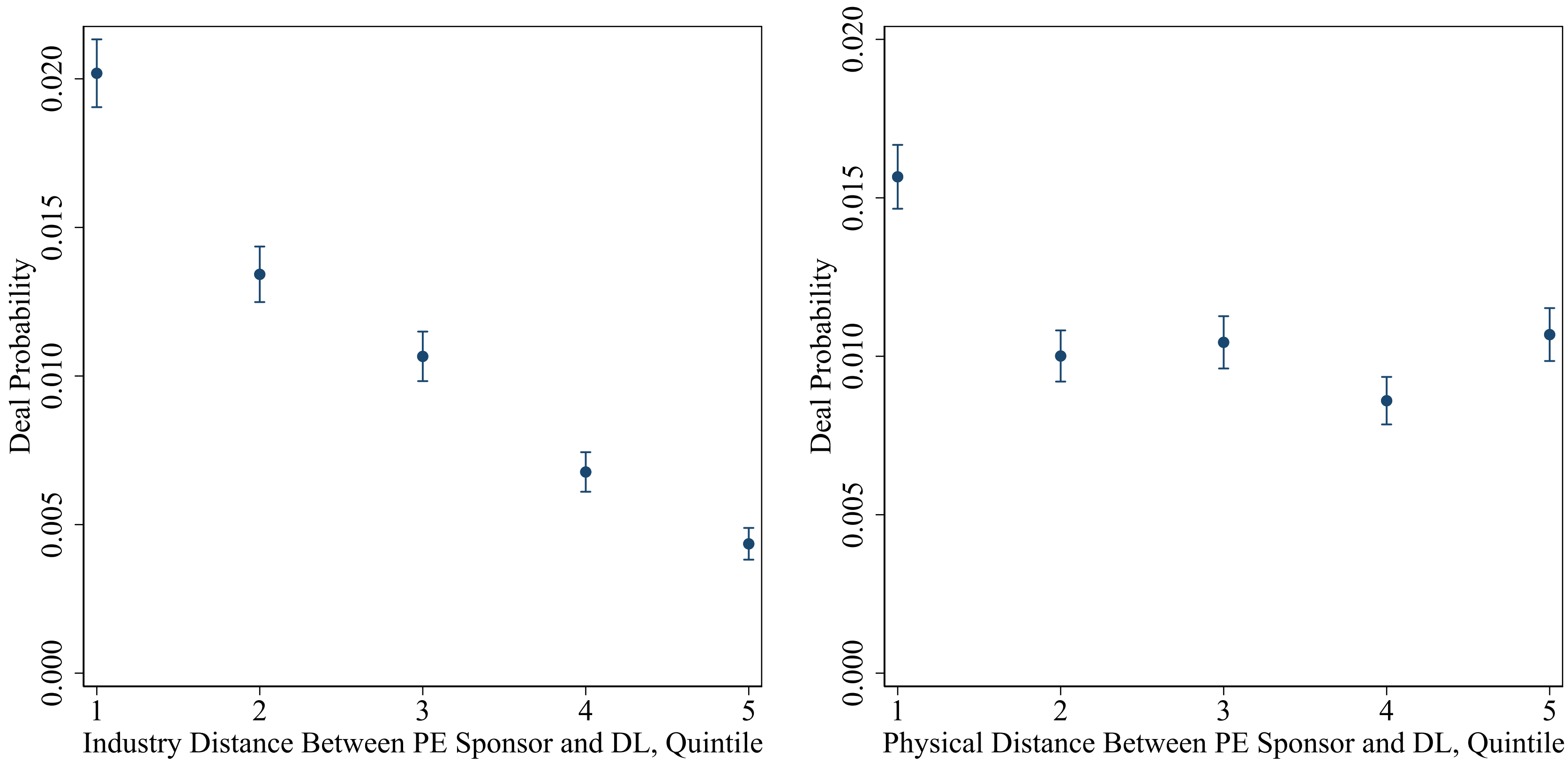


Figure 9: Distance Effects on Deal Probability



The two panels present bin-scatters of the probability of a deal between a direct lender and a PE sponsor by industry distance (left panel) and physical distance (right panel).

Internet Appendix

A UCC Data Description

A.1 Representativeness of Middle-Market Lending

Gopal and Schnabl (2022) demonstrate that Uniform Commercial Code (UCC) filings capture a substantial portion of small business lending. An open question is whether this extensive coverage extends to the middle-market segment, which is the focus of our study. While small businesses often rely on bilaterally negotiated loans from banks, finance companies, and fintech lenders, middle-market firms also borrow through broadly syndicated loans arranged by banks and through direct lending by private credit funds and Business Development Companies (BDCs).

Despite the importance of these lending channels, the coverage and representativeness of UCC filings on the broadly syndicated and direct lending markets have not been systematically examined. This appendix addresses that gap by cross-validating the UCC dataset against established data sources widely used in the literature.

The goal of this study is to measure relationship-based, information-sensitive loans to middle market firms, where the lender in question is doing the monitoring and screening. Do UCC filings capture such loans by direct lenders? This is a challenging question to answer, as it requires data on a set of loans where we know for sure that a direct lender is originating the loan. The best test we have for this uses a proprietary dataset from Jang (2025), which identifies direct loans as those arranged by a direct lender, based on lead lender information extracted directly from credit agreements. Jang (2025) provides considerable evidence that the direct lenders on these loans are monitoring and screening the borrower. From this dataset, we randomly sample 100 direct loans made to US-headquartered borrowers between 2014 and 2022.

We find that 100% of borrowers appear in the UCC dataset. Of these, 85% (87%) have a filing by the lender within a year (or within the five-year window), and an additional 6% (9%) have a filing by another lender in the same year (or within the five-year window). We view this as the strongest confirmation that direct lenders making relationship-based, information-sensitive loans file a UCC filing that we can measure.

In terms of syndicated loans, UCC filings are made by creditors who hold a secured claim on a borrower's collateral. Importantly, not every lender in a syndicate is required to file, raising several important questions: Which lenders within the deal syndicate typically file UCCs? Do relationship lenders tend to file, or are filings rather made by entities with limited economic exposure to the borrower? The value of UCC data in capturing borrower-lender relationships depends heavily on answering these questions.

Our UCC dataset spans from 2006 to 2023. To evaluate its coverage of the broadly syndicated loan market, we randomly sample 100 Dealscan deals involving US-headquartered borrowers in the same period. Dealscan provides loan-level data at the lender level, yielding a sample of 100 lead lenders and 293 participant lenders. Following Sufi (2007) and Ivashina (2009), we define lead lenders as the administrative agent or, if not specified, one of the arrangers.

We find that 95 out of the 100 borrowers (95%) appear in the UCC dataset. Furthermore, 62% of the lead lenders have a corresponding UCC filing dated within two years before or after the loan origination year. We use this five-year lookup window to account for the fact that UCC filings may not be made every time the loan is originated or refinanced, although they must be renewed every five years. In contrast, only 8.2% of participant lenders (24 out of 293) file within this window. These results suggest that UCC filings are effective at capturing the presence of lead lenders, who are the entities most likely to maintain long-term relationships with borrowers.

We next evaluate UCC coverage of private credit by examining 100 randomly selected private credit deals involving US-headquartered borrowers from PitchBook. Unlike Dealscan, PitchBook does not distinguish between lender roles. We find that 98% of these borrowers appear in the UCC dataset. In addition, 44% of borrower-lender pairs have a corresponding UCC filing within the five-year window. Prior research by Haque, Mayer and Stefanescu (2025a) shows that direct lenders also participate in syndicated deals. Consistent with this finding, we observe that 92% of the PitchBook borrowers have some UCC filing within the five-year window, 44% have a filing by the same lender within the window, and an additional 48% have a filing by another lender during the same period.

A.2 Processing Data

Our data vendor, MailingLists, provides two datasets: one including *dunsnumbers* for both borrowers and lenders, and one without. To maximize coverage, we sequentially applied a series of algorithmic procedures to supplement missing *dunsnumbers*: first, exact name matches (Algorithm 1); next, partial name and address matches using the first five letters (Algorithm 2); and finally, partial name and ZIP code matches using the first ten letters of the name (Algorithm 3). These sequential procedures substantially improved coverage, raising lender *dunsnumber* coverage to a yearly average of 95% and borrower *dunsnumber* coverage to a yearly average of 75%, compared with the original yearly averages of 58% and 39%, respectively. Table A1 reports the year-by-year improvements in coverage.

A.3 Lender Classification

We then classify direct lenders using a list of U.S. private credit funds from PitchBook and Preqin, matched to NETS through phone numbers and manual name verification. We supplement this with a keyword search for variations of “direct lending,” “private credit,” “debt fund,” and “lending fund,” and excluding obvious false positives such as “tax credit fund.” Validation on a random sample of 200 filings suggests a false positive rate of only 1.5%.

Table A1: Coverage Improvement in *dunsnumber*

	Lender *dunsnumber*				**Borrower *dunsnumber***			
Year	**Original**	**Algo 1**	**Algo 2**	**Algo 3**	**Original**	**Algo 1**	**Algo 2**	**Algo 3**
2006	54.28%	94.62%	95.18%	95.47%	44.02%	73.05%	78.09%	79.49%
2007	48.65%	95.40%	95.93%	96.18%	41.32%	70.67%	75.66%	77.06%
2008	49.01%	95.58%	96.10%	96.35%	42.24%	71.54%	76.47%	77.92%
2009	59.45%	95.93%	96.44%	96.70%	54.21%	78.98%	84.70%	85.92%
2010	31.60%	95.88%	96.47%	96.70%	45.41%	77.39%	83.09%	84.39%
2011	56.03%	96.65%	97.17%	97.39%	46.76%	75.03%	80.66%	81.87%
2012	69.65%	96.77%	97.25%	97.59%	47.78%	72.85%	78.00%	79.19%
2013	70.97%	96.57%	97.06%	97.47%	45.12%	70.88%	76.92%	78.26%
2014	69.54%	96.37%	96.87%	97.32%	43.60%	70.07%	76.56%	78.06%
2015	67.56%	96.01%	96.52%	96.99%	41.83%	68.34%	74.52%	76.04%
2016	66.37%	95.46%	95.91%	96.34%	38.17%	67.93%	73.76%	75.18%
2017	70.34%	95.25%	95.73%	96.19%	39.27%	65.87%	71.82%	73.23%
2018	66.79%	94.56%	95.13%	95.54%	35.80%	63.82%	69.94%	74.47%
2019	55.49%	93.83%	94.51%	94.80%	27.11%	61.11%	67.47%	69.26%
2020	57.64%	94.87%	95.59%	95.80%	26.03%	57.13%	62.75%	64.59%
2021	55.03%	93.17%	94.11%	94.36%	22.90%	54.22%	60.30%	62.14%
2022	38.74%	86.65%	87.71%	88.07%	19.89%	54.70%	60.47%	62.33%

Banks are identified using parent-level NETS NAICS codes (522110 Commercial Banking, 522130 Credit Unions, and 522180 Savings Institutions and Other Depository Credit Intermediation), keyword searches (e.g., names ending in “BK” or containing “bank,” “credit union,” “savings & loan,” or “S&L”), and a list of some of the largest banks.[19] Validation on a random sample of 200 filings indicates a 0% false positive rate.

Finance companies are identified through parent-level NAICS codes (522220 Sales Financing, 423820 Farm and Garden Machinery and Equipment Merchant Wholesalers, and 522291 Consumer Lending), keyword searches (e.g., “leasing,” “financial services,” “equipment financ,” “finance company”), and a list of some of the largest finance companies.[20] The false positive rate for

[19]This list includes the top 25 banks from Call Reports (JP Morgan, Bank of America, Citi, Wells Fargo, Wachovia, US Bank, PNC, Truist, Capital One, TD, BNY Mellon, Charles Schwab, Morgan Stanley, State Street, Goldman Sachs, Fifth Third, Northern Trust, HSBC, Citizens, Mizuho, KeyBank, and Huntington) as well as Ally Financial, Credit Suisse, and Deutsche Bank.

[20]This list includes the top 10 finance companies from Gopal and Schnabl (2022) (John Deere, CNH Capital, Kubota, GE Capital, Caterpillar, Snap-On Credit, DLL Finance, AGCO Finance, Tower Loan, Toyota Motor Credit) as well as Republic Finance, Gulfco Mississippi, Volvo Finance, Mercedes-Benz Finance, First Heritage Credit, 1st Franklin Financial, Komatsu Financial, Rabo Agrifinance, and Automotive Finance Corp.

finance companies on a random sample of 200 filings is 3.5%.

Compared with Gopal and Schnabl (2022), our data processing and lender classification approach achieves noticeably higher coverage, identifying 576,925 bank filings and 429,658 finance company filings in 2016, compared to 497,254 and 389,786, respectively, in their dataset.

B Identifying PE ownership using Google Vertex AI

This appendix describes our methodology for measuring PE ownership using Google Vertex AI. The Google Vertex AI dataset supplements traditional private equity databases by systematically identifying evidence of PE ownership through analysis of web-based information.

B.1 Introduction to Google Vertex AI and Grounding with Google Search

Google Vertex AI is a unified artificial intelligence platform that integrates Google Cloud's AI and machine learning services within a single environment. The platform provides access to Google's **Gemini** family of large language models, which are designed for multi-step reasoning, nuanced language understanding, and synthesis of information from multiple sources.

In this study, we employ the **Grounding with Google Search** feature—a capability within the Gemini framework that connects the model to real-time web content. This integration enables the model to base its responses on current, verifiable information rather than relying solely on static training data. When a prompt is sent to the Gemini API with the *google_search* tool enabled, the model analyzes the query, issues one or more web searches, processes the retrieved results, and generates a grounded response. Each response includes structured grounding metadata—such as executed search queries, URLs of cited sources, and text segments supporting each claim—thereby enhancing transparency and enabling verification of factual accuracy.

We implement this functionality through a structured pipeline built on Google's Generative AI API within Vertex AI to identify whether each firm in our dataset is owned by a PE sponsor between 2018 and 2022. For every firm, the system constructs a standardized prompt that includes the company's name, address, and location, and instructs Gemini to determine whether the firm was private-equity-funded during this period. The prompt directs the model to search the web for ownership information, consider both direct and indirect (parent-level) PE ownership, exclude entities that merely invest in PE funds, and provide a brief explanation citing supporting evidence. To ensure consistent and machine-readable outputs, the model is required to return a valid JSON object containing (i) a binary indicator of PE ownership and (ii) the name of the corresponding private-equity sponsor(s). Any deviation from this format triggers automatic re-processing.

All production runs employ a fixed configuration to ensure consistent behavior. Specifically, we use the **gemini-2.5-pro** model with a thinking-budget allocation of 128 tokens and a maximum output length of 1,024 tokens. These parameters provide a practical balance between accuracy and efficiency, enabling the model to generate structured, verifiable outputs while maintaining manageable inference costs.

B.2 Limitations of Traditional Database Matching and Advantages of Google Vertex AI with Grounding

PitchBook's coverage is extensive, but we have found it quite difficult to match the data to NETS. Crucially, to ensure accuracy, our matching methodology relies on exact or near-exact matches between company identifiers in the NETS data set and entries in PitchBook's proprietary database. Our dataset provides both company names and addresses for matching, which should theoretically strengthen match accuracy. However, our manual validation revealed that even when company names matched identically between our dataset and PitchBook's web version, the registered addresses often differed. This mismatch stems not from PitchBook's incomplete capturing of PE relationships—which it documents thoroughly for entities within its system—but rather from the inherent limitations of structured field-matching algorithms when applied across heterogeneous datasets. These matching difficulties are compounded when firms use different legal names, have changed their registered addresses over time, or operate under parent company structures.

Our manual validation confirms that the limitation arises not from incomplete PitchBook coverage—which remains extensive and detailed—but from the rigidity of structured field-matching algorithms when applied across heterogeneous datasets. Among thirty randomly selected firms, twenty-one (70%) were verifiably private-equity or venture-capital backed between 2018 and 2022, yet only four (13%) were flagged as such in the merged dataset. However, when searching directly on PitchBook's web interface—using combinations of firm names, historical or parent-company names, alternative operating names, or registered addresses—we were able to recover accurate financing information or related investment histories for nearly all cases. Of these twenty-one verified cases, eleven (52%) could be confirmed by searching the firm's own or a closely related name, while the remaining ten (48%) required searches through the parent company, subsidiary, or alternative identifiers such as address or legacy entity name. Appendix Section B.3 provides detailed firm-level illustrations.

This evidence indicates that PitchBook correctly documents the relevant ownership relationships, but matching limitations to NETS are unavoidable. First, even though both datasets apply standardized naming and address conventions, deterministic matching remains limited by structural variations in legal entity names, causing the same firm to appear under slightly different identifiers across datasets. Second, firm identities evolve over time, and such temporal changes generate discrepancies across datasets compiled at different points. Corporate rebranding, name changes following acquisitions, and shifts in headquarters locations mean that firms appearing under one identifier in PitchBook may be listed under another in NETS. Third, although PitchBook's web interface provides comprehensive information at the parent-company level, it often omits small or subsidiary entities that are not separately listed as portfolio companies. In contrast, NETS records these operating subsidiaries under their own names. As a result, when a subsidiary's name appears in NETS but only the parent entity is captured in PitchBook, the match cannot be established without an explicit cross-reference between the two.

To address these limitations, we turned to the Gemini-based approach, which offers a few advantages. First, by leveraging real-time web search, Gemini accesses a broader and more current information base than any single proprietary database. The model retrieves ownership information from multiple sources—including company websites, SEC filings, press releases, industry publications, and news articles—thereby triangulating evidence across documents that may not be systematically indexed in traditional databases.

Second, Gemini can identify PE ownership through parent company relationships and transitive ownership structures, effectively bridging the gap when direct field matches fail. Third, the web-grounded approach is inherently more flexible with respect to name variations, address changes, and parent-subsidiary relationships. Rather than requiring exact matches on predetermined fields, Gemini can reason about whether two entities refer to the same organization despite discrepancies in how they are referenced across sources. This flexibility proved particularly valuable when the entity name or address in our dataset differed from information in transaction announcements or when ownership was held at the parent company level.

Finally, the prompt-driven methodology allows researchers to specify nuanced criteria—such as the relevant time period (2018–2022), the distinction between direct PE ownership and passive fund investment, and the inclusion of indirect ownership through parent companies—ensuring that the classification aligns precisely with our research question.

Of course, the Gemini-based approach also suffers drawbacks. For example, as described below, the Gemini-based approach yields a false positive rate that we hope to address in future versions of this study. In addition, we explored using the Gemini-based approach in historical data, attempting to track whether firms in NETS as of 2007 were owned by a PE sponsor at some point between 2003 and 2007. The Gemini-based approach in the historical data yielded an unacceptably high false positive rate, which we surmise is due to difficulties for Gemini in accurately identifying information from 20 years ago. The approach works quite well in more recent data, but our experience suggests worse performance in historical data. But overall, we believe the idea of using the extensive information on the internet to identify whether a firm is owned by a PE sponsor is promising for future research.

B.3 Manual Audit of PitchBook–NETS Matching Errors

To better understand the sources of mismatch between PitchBook and NETS, we conducted a detailed manual audit of 21 firms from our study sample that received funding (either directly or indirectly) between 2018 and 2022. In the merged PitchBook-NETS dataset, only 4 of these 21 firms (19%) were correctly identified as PE- or VC-backed (3 PE and 1 VC). However, manual verification using the PitchBook web interface revealed that investment information was available for nearly all cases.

Each case was reviewed by our research assistants using the PitchBook website and supplementary public information to determine whether the firm received private equity or venture capital investment between 2018 and 2022, and to diagnose the specific reason for linkage failure.

B.3.1 Category 1: Direct Matches with Complete Information

Five firms exhibited exact or near-exact matches in both company name and address between the two databases, yet were not identified as PE-backed in the merged dataset. These failures likely stem from outdated metadata in the exported PitchBook dataset or technical issues during the matching algorithm execution. For example, *Allied Group Inc* appeared in both databases with consistent information but failed to link during the merge process.

B.3.2 Category 2: Name Variations and Alternative Operating Names

Five firms appeared under slightly modified legal or operating names. For instance, *Seracare Lf Scnces Hldings Llc* in NETS corresponds to *SeraCare* in PitchBook, while *Pyramid Lqr Management LP* operates as *Pyramid Hotel Group* in PitchBook records. Similarly, *AOG LLC* conducts business as *Tandem Foods* (formerly *TruFood*), and *Diversified Industries Inc* operates as *Diversified Pump & Compressor* in PitchBook.

B.3.3 Category 3: Historical Name Changes and Rebranding

One firm changed its legal identity following significant corporate restructuring. *Curtis Bay Energy Inc* was acquired and renamed *Sharps Medical Waste Services*. PitchBook correctly recorded the successor company name, whereas NETS maintained the predecessor record, resulting in an apparent mismatch despite continuous PE ownership throughout the period.

B.3.4 Category 4: Address Discrepancies

Three firms shared exact or nearly exact legal names with their PitchBook counterparts but differed in address entries due to headquarters relocation, suite-level changes, or alternative registration addresses. For example, *Lakeview Health*, *Suuchi Inc*, and *PlanStreet Inc* all appeared with correct names but mismatched addresses.

B.3.5 Category 5: Combined Name and Address Discrepancies

One firm exhibited mismatches in both name and address fields. *Titan Security Services Inc* appears in PitchBook as simply *Titan Security*, and the recorded addresses also differed, creating a double barrier to successful matching.

B.3.6 Category 6: Indirect Ownership via PE-Backed Parent Companies

Four firms were subsidiaries or operating units of larger corporate groups under PE control. PitchBook typically tags the parent entity as "Private Equity-Backed" but may label subsidiaries as "Corporate Backed or Acquired", thereby masking indirect PE ownership relationships within multi-tiered structures. For example, *11 Carmine Tacos LLC* operates the *Tacombi* restaurant brand and is owned by a PE-backed parent company. Similarly, *CDI Management Corp* operates as part of *Rayus Radiology*, and *Future Technologies Group LLC* is corporate-backed by *New Era Technology*, which itself is PE-backed. Manual verification of parent company names on the PitchBook website confirmed PE backing for three of these four cases; the fourth case (*North Fort Myers Fclty Oprtons*, operating under *Consulate Health Care*) has since exited PE ownership.

B.3.7 Category 7: Special and Structural Cases

Two entities represent special structural situations. First, GPIF SIRATA LLC functions as a special-purpose vehicle used by PE sponsors to hold operating assets. Because PitchBook's structured data export often omits these intermediate holding entities, the connection to PE sponsors appears only at the parent level, leading to undercounting of PE involvement. Second, Wealth Enhancement Group LLC illustrates an ambiguous case in which PitchBook's website interface does not show the financing status of this firm. Manual verification reveals evidence of multiple PE transactions during the study period. In July 2019, TA Associates acquired Wealth Enhancement Group from Lightyear Capital LLC, which had been the majority owner since 2015. Later, in August 2021, Onex Corporation—through its private equity arm Onex Partners V—acquired a substantial stake, becoming an equal capital partner alongside TA Associates. The likely explanation is that financial terms were not disclosed for either transaction, as explicitly stated in contemporary press releases. Without disclosed deal values or valuations, PitchBook's automated financing status fields may remain unpopulated, despite the transaction details being available through manual database searches.

B.4 Manual Validation of the Gemini-Based Classification

To validate the accuracy of the Gemini-based classification, we conducted a manual review of 88 firms randomly selected from our dataset. Two research assistants independently examined each case using web search and the PitchBook web interface to verify ownership status during the 2018–2022 period.

Manual review revealed that of the 60 cases where Gemini identified PE ownership, 54 were confirmed as accurate, yielding 6 false positives (10% false positive rate). Of the 28 cases where Gemini indicated no PE ownership, all 28 were confirmed correct (0% false negative rate). Overall, the model achieved a 93.2% accuracy rate (82 of 88 correct classifications).

Analysis of the six misclassified cases revealed three primary sources of error. First, some cases involved confusion between firms with similar names or shared physical addresses, where

Gemini incorrectly attributed one company's PE backing to another entity at the same location. Second, certain cases involved misattribution of acquisitions by publicly traded corporations as private equity transactions, particularly when the acquiring company had historically been PE-backed but had since gone public. Third, in a few instances, Gemini relied on outdated ownership information that was no longer valid during the 2018–2022 study period.

We view this Gemini-based approach as a work in progress, and we are working hard (1) to improve the Gemini-based match, and (2) to better match PitchBook with NETS to understand why there are discrepancies.

C Appendix Tables and Figures

Table A2: Fraction of Firms with a Loan, by Firm Size

	N	Banks	Finance Companies	Direct Lenders (UCC)	BDC	Private Credit (Pitchbook)	Private Credit (Broad)
Private							
3-5	4627970	0.0696	0.0291	0.0006	0.0002	0.0001	0.0008
6-10	2005054	0.0986	0.0359	0.0011	0.0002	0.0001	0.0013
11-20	547092	0.2232	0.0808	0.0031	0.0008	0.0004	0.0037
21-50	317840	0.3039	0.1153	0.0071	0.0022	0.0014	0.0089
51-100	90437	0.3688	0.1557	0.0153	0.0063	0.0040	0.0203
101-200	34999	0.4480	0.2071	0.0272	0.0138	0.0100	0.0360
201-500	18105	0.5048	0.2552	0.0400	0.0287	0.0185	0.0581
501-1000	5288	0.5783	0.3359	0.0613	0.0526	0.0304	0.0910
1001-2000	2514	0.6492	0.4300	0.0684	0.0784	0.0374	0.1213
2001-5000	1582	0.7345	0.5436	0.0860	0.1087	0.0512	0.1631
>5000	701	0.8645	0.7546	0.1098	0.1469	0.0471	0.2097
Public							
	4437	0.5691	0.4172	0.0951	0.1521	0.0336	0.2132

The last column, private credit (broad) reflects the fraction of firms with any private credit investment. That is, with either a UCC filing, a BDC investment, or a private credit investment from PitchBook.

Table A3: Firm Counts by Direct Lending Source

Lending Source Category	Full Sample	Private Middle Market
Only UCC	10,874	4,181
Only BDC	2,787	1,089
Only PB	697	353
UCC & BDC	989	562
UCC & PB	549	381
BDC & PB	740	381
UCC & BDC & PB	795	525

Notes: