Human Capital in Financial Contracting *

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[Preliminary, Please Do Not Circulate]

Abstract

This paper examines the role of human capital in the design of bank and private credit agreements. We measure human capital across three core functions of credit intermediation: due diligence, sourcing, and risk management/approval. We document that private credit (PC) lenders specialize more in due diligence human capital, whereas banks focus more on the other two functions. Our central result is that PC-originated loans feature more customized contractual terms—particularly with respect to the most heavily negotiated covenants—and these differences are largely explained by the observed human capital differences. We further show that human capital increasingly flows from banks to non-banks, concentrated among employees with diligence expertise, who are rewarded with higher seniority and compensation upon transitioning.

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1 Introduction

With the rise of private financing, especially, from private equity and private credit funds, hereafter referred to as non-banks, we study credit provision technologies of non-bank intermediation relative to that provided by banks. We focus on the private credit market, which has been the fastest growing asset class providing an important source of debt capital to middle-market firms.[1] While prior research has largely focused on the drivers of this growth (Chernenko, Erel and Prilmeier, 2022; Davydiuk, Marchuk and Rosen, 2024; Buchak, Matvos, Piskorski and Seru, 2024; Jang, Kim and Sufi, 2025; Robinson and Wallskog, 2025), surprisingly little is known about the role of human capital, i.e., the individuals employed at the lender firms at the time of loan contracting, in explaining differences in credit provision by banks and private credit funds. The rapid influx of financial capital implies significant investments in human capital, yet how these investments shape financial intermediation remains poorly understood. Do banks and private credit lenders differ in their human capital? How do these differences influence their intermediation activities, such as the contracts they design?

In this paper, we leverage a novel database and develop a new measurement methodology to study the role of human capital in the design of bank and private credit agreements. Studying these questions poses challenges on both the data and measurement fronts. We address the human capital data challenge by relying on position-level job description data from Revelio Labs, a repository of public LinkedIn profiles. To the best of our knowledge, this is the first paper to measure human capital in the financial intermediation sector across several functions, such as sourcing, diligence, and risk approval. We construct contract customization and specialization measures using financial and informational covenants in individual loan credit agreements of bank and private credit providers. Our measures, in part, capture monitoring methods used by financial intermediaries. We show that firms with individuals in more diligence roles write more customized contracts. These lender firms are primarily private credit providers, and include more informational and monitoring covenants in contract underwriting. We discuss the implications of specialized deal contracting for the evolution of career trajectories of individuals writing the contracts. We observe substantial movements of individuals from diligence roles in banks to private credit funds, being rewarded with senior roles and higher compensation.

To measure lender human capital, we use workforce data from Revelio Labs, which provides granu-

[1] The private credit industry has expanded roughly tenfold over the past two decades, growing from under $200 billion in 2007 to nearly $2 trillion in 2025 in the US alone. While we focus on private credit, 70% of private credit intermediation is sponsored by private equity firms. For more information on private credit and private equity overlap, refer to link.

lar information on individual employees' job titles, descriptions, and career histories across firms. Using job descriptions, we classify each employee into one of three core lending functions—sourcing, diligence, and risk/approval—and construct firm-year measures of functional composition (the share of classified employees in each role) and function-specific experience (average years of prior experience per classified employee). Our matched sample covers 2,104 private credit and 6,068 bank firm-years from 2014 to 2023. We find that banks allocate a greater share of their workforce to sourcing and risk/approval, while private credit firms are more diligence-intensive. Banks also accumulate more sourcing and risk/approval experience per employee, whereas private credit firms develop a comparative advantage in diligence experience. These organizational differences are stable over time and persist after controlling for firm size and age, suggesting fundamentally distinct models of human capital deployment in the lending process.

As private credit lenders and banks primarily compete for private firms, which are mostly private equity-backed firms (Block, Jang, Kaplan and Schulze, 2024; Jang et al., 2025), their loan contracts are not available in standard sources used in prior literature, such as SEC Edgar filings for publicly listed firms. We obtain our sample of credit agreements from an anonymous third-party appraisal firm specializing in private capital valuations, previously used by Jang (2025); Jang and Kim (2025), who demonstrate its representativeness of private credit deals. We then apply a state-of-the-art text-based methodology developed by Murfin and Sun (2025) to measure the customization of hundreds of loan term definitions, and extend their approach to focus specifically on the most heavily negotiated information, financial, and negative covenants.

Our analysis of loan contracts covers 2,347 agreements, including both bank-originated and PC-originated loans from 2014 to 2023, using the full contract text rather than high-level summaries. We examine six primary measures of contract design to capture different dimensions of customization. First, using hundreds of contractual terms defined in the contract, *similarity* measures how closely a contract resembles a standard boilerplate agreement, while *novelty* captures the presence of unusual or nonstandard terms. Second, we evaluate financial covenant customization using the *EBITDA distance*, which reflects how negotiated definitions of EBITDA deviate from common standards. Third, *negative covenant distance* quantifies customization in clauses that restrict borrower actions, including limitations on indebtedness, investments, and payouts. Finally, we measure monitoring intensity through the presence of *monthly financial* reporting requirements and *board observation* rights, which capture lenders' ongoing involvement in overseeing borrower performance.

Our results show that PC-originated loans are more customized than bank-originated loans across all six measures. Despite including fewer total terms, nonbanks incorporate more novel provisions, use contractual definitions—including EBITDA and negative covenants—that deviate further from boilerplate, and impose stronger monitoring through monthly financials and board observation rights. These differences persist even after controlling for borrower characteristics, indicating that non-bank lenders actively tailor contracts rather than simply replicating standard agreements.

Next, we link these patterns of contract customization to the human capital of lenders. Lenders with a higher share of employees focused on diligence human capital design more customized contracts, and this effect is particularly driven by private credit lenders. Once human capital differences are accounted for, the apparent advantage of private credit lenders diminish, suggesting that their customization reflects specialized expertise rather than organizational or technological factors alone. Overall, our findings highlight that contract innovation in private credit markets is driven by the interplay of lender type and human capital, shaping both the structure and monitoring of middle-market loans.

Finally, we examine the labor market implications of these human capital differences. We document a sustained net outflow of intermediation-related human capital from banks to non-banks, concentrated among employees with prior diligence expertise. Bank-to-nonbank transitions account for a growing share of all firm transitions over our sample period, and the net flow is strongest for diligence-specialized workers. Importantly, employees who move from banks to non-banks with prior bank diligence experience receive approximately 9.4% higher seniority and 9.5% higher total compensation relative to other transitioners, with each additional year of prior bank diligence experience associated with a 3.2% seniority increase and a 4.1% compensation premium. These returns are the largest for diligence expertise—prior sourcing or risk/approval experience does not yield comparable compensation gains upon transition. Together, these findings suggest that due diligence skills acquired in banks are portable and highly valued in the private credit sector. Furthermore, the growth of private credit is partly sustained by a reallocation of specialized human capital away from banks. This paper has important implications for contract underwriting in financial intermediation and hiring of individuals by firms supporting these tasks.

Literature Review. We contribute to multiple strands of literature. First, we speak to the growing body of research on nonbank intermediation. In particular, a recent literature examines the economic differences between bank lending and private credit in corporate credit markets (Chernenko et al., 2022; Jang, 2025; Haque, Mayer and Stefanescu, 2025; Jang et al., 2025; Robinson and Wallskog, 2025). These

studies show that banks and private credit lenders differ in the types of borrowers they serve, as well as in loan seniority and collateral structures. However, in the case of private equity–backed firms—where private credit lenders are most active and compete most directly with banks—private credit lenders engage more intensively in information-based activities such as monitoring and relationship lending, areas traditionally viewed as deposit-financed banks' comparative advantage (Diamond and Rajan, 2001). We extend this literature by providing richer evidence that private credit lenders customize loan contracts to a greater extent, and by highlighting differences in human capital, along with the migration of such talent from banks to private credit lenders, as a key mechanism underlying these differences in contractual customization.

Second, we contribute to the literature on human capital. Recent research has discussed multiple forms of intangible capital, amongst which the closest to our research is the importance of human capital in performance, valuation, and contracting (Jackson (2025), Beaumont, Hébert and Lyonnet (2025), Binfarè, Brown, Harris and Lundblad (2023), Bolton, Wang and Yang (2019), Guan, Li, Lu and Wong (2019), Ewens and Rhodes-Kropf (2015), Guenzel, Kogan, Niessner and Shue (2025)).[2] Our main contribution is the measurement of human capital in financial intermediation across distinct functions: due diligence, sourcing, and risk management/approval. These functions are not interchangeable, making it important to measure them separately. In particular, we find that PC lenders invest more heavily in due diligence human capital, whereas banks focus more on sourcing and risk management/approval roles.[3] This distinction has implications not only for the types of contracts an intermediary designs but also for the portability of expertise when individuals move between institutions that specialize in different functions.

Lastly, our paper contributes to the literature on financial contracting in private firms. Much of the existing research on debt contracts has focused on publicly traded firms, primarily due to data availability (Chava and Roberts, 2008; Roberts and Sufi, 2009; Nini, Smith and Sufi, 2012; Ivashina and Vallée, 2025). At the same time, a large body of work has documented the economic importance and real effects of private equity–backed firms (Kaplan and Stromberg, 2009; Davis, Haltiwanger, Handley, Jarmin, Lerner and Miranda, 2014; Mittal, 2024; Isen, Richmond, Smith and Yannelis, 2025). Building on Jang

[2]For further research on other forms of intangible capital, refer to Eisfeldt and Papanikolaou (2014), Eisfeldt, Kim and Papanikolaou (2022), Ayyagari, Demirgüç-Kunt and Maksimovic (2024), Crouzet and Eberly (2023), Crouzet, Eberly, Eisfeldt and Papanikolaou (2022). For customer capital, refer to, He, Mostrom and Sufi (2024), Gourio and Rudanko (2014). This is not an exhaustive list of papers.

[3]Another strand of literature examines real effects of diligence function (Giroud (2013), Bernstein, Giroud and Townsend (2016), Fu and Taylor (2025)).

(2025), who highlight the extensive use of financial covenants as a key monitoring tool in private markets, we show that private loan contracts are highly customizable to borrower needs. Specifically, we extend on state-of-the-art NLP techniques to measure the customization of hundreds of loan term definitions (Murfin and Sun, 2025), as well as the most heavily negotiated information, financial, and negative covenants.

2 Data and measurement

Our analysis combines two novel data sources. First, we use employer–employee histories from Revelio Labs to measure human capital involvement in lending at both banks and private financing intermediaries, covering 663 banks and 235 nonbanks with 4,115,241 and 486,964 unique individuals respectively from 2014 to 2023. Second, we obtain private credit agreements from a proprietary data provider that allow us to measure contract customization and innovation for both private credit and bank loan contracts, comprising 1,586 PC loans and 761 bank loans over the same period. We describe these main data sources and measurement below. Additional details are in Appendix A.1.

2.1 Human capital

We obtain individual-level employment histories for employees at both banks and nonbank from Revelio Labs. Revelio Labs scrapes data from Linkedin profiles and provides longitudinal records for each professional's employment history, job titles, start and end dates, job location, etc. Revelio Labs also keeps each person's own job descriptions, which we use to classify their job roles into due diligence, sourcing, and risk approval. We match each lender to Revelio's ultimate parent firm identifier, which aggregates all subsidiaries under a single parent entity. This ensures comprehensive coverage of each lender's workforce—for example, KKR's parent identifier gives us positions across all KKR subsidiaries (e.g., KKR Credit Advisors, KKR Capital Markets), rather than only positions filed directly under the subsidiary entity. We use detailed position-level data to identify the type of human capital at banks and other financial intermediaries, construct measures of officer experience and mobility, and quantify officer industry specialization based on the industry composition of prior deals and employers. To obtain the list of banks and and nonbank, we rely on Pitchbook.

In this section, we describe our classification of human capital in different functions of financial intermediation. We focus on our list of banks and non-banks we match to the credit agreement sample

and use in Section 3.2. We obtain job histories of individual employees at these firms from Revelio. We have 4,115,241 (486,964) unique employees employed at banks (nonbank) between 2014 and 2023. We categorize individuals employed at firms into three broad job functions—sourcing, dilligence, or risk/approve—using job descriptions on their Linkedin profiles. We have job descriptions for 47.8% (47.9%) of employees in banks (nonbank). We manually classify employees across functions and industries. Our methodology is described in Appendix A.2.[4]

To show that our classification leads to reasonable classifications of employees' job functions, we plot word cloud of keywords appearing in both our bank and nonbank samples. Our word cloud of intermediation-function keywords (Figure 1) suggests that the classification captures meaningful differences between bank and nonbank: bank descriptions emphasize sourcing, risk management, and formal approval processes, while PC descriptions are more heavily weighted toward due diligence, deal structuring, and credit analysis.

Figure 1: Word Cloud (Keywords Only)



Notes: This figure displays word clouds of intermediation-function keywords in job descriptions for bank (left, blue) and PC (right, orange) lenders. Word size reflects the frequency of each keyword within that lender type. Keywords are restricted to predefined intermediation-function stems spanning sourcing, screening, underwriting, approval, risk management, and monitoring. Matching uses subword logic (e.g., "analy" matches analysis, analytical, etc.). The sample is restricted to positions classified as having a lending intermediation function. Data are from Revelio Labs job descriptions matched to PitchBook lenders.

After classifying individuals' job functions, we construct a person-firm-year panel tracking each employee's job history across banks and nonbank. We then aggregate to the firm-year level to build two sets of human capital measures based on the three broad job functions described above. First, we compute function shares: for each firm-year, the number of employees in a given function divided by the total number of employees with any classifiable job function. This captures the degree to which a firm's workforce specializes in sourcing, due diligence, or risk/approval.

Second, we compute function experience intensity: for each firm-year, the total years of prior expe-

[4]We allow one role to be classified into more than one function.

rience in a given function accumulated across all employees, divided by the number of employees with any classifiable job function. This captures the depth of expertise a firm's workforce brings to each function. Table 1 Panel A presents key summary statistics for these human capital variables at the firm-year level.

Banks allocate a larger share of classified employees to sourcing (mean 0.64 vs. 0.53 for PC) and risk/approval (0.40 vs. 0.32), while PC firms have a higher diligence share (0.67 vs. 0.60). Turning to experience, PC employees accumulate more diligence experience per classified employee (5.62 years vs. 4.55 for banks), whereas banks have more sourcing experience (5.21 vs. 4.63) and risk/approval experience (3.13 vs. 2.39) per classified employee. These patterns are consistent with banks allocating relatively more human capital to origination and ongoing risk oversight, while nonbank concentrate personnel and experience in due diligence and credit evaluation.

Table 1: Summary Statistics

Panel A: Private Credit

	N	Mean	P25	Median	P75	SD
Sourcing share	2,104	0.53	0.36	0.55	0.72	0.29
Diligence share	2,104	0.67	0.52	0.68	0.85	0.26
Risk/Approval share	2,104	0.32	0.14	0.32	0.43	0.25
Sourcing experience	2,104	4.63	2.31	3.84	5.82	3.97
Diligence experience	2,104	5.62	2.70	4.62	7.00	4.67
Risk/Approval experience	2,104	2.39	0.58	1.75	3.08	2.78
PE fund size share	2,104	0.40	0.00	0.29	0.81	0.40
Log firm age	2,104	1.51	1.10	1.70	2.08	0.69
Log classified employees	2,104	3.03	1.39	2.30	4.37	2.11

Panel B: Banks

	N	Mean	P25	Median	P75	SD
Sourcing share	6,068	0.64	0.54	0.67	0.75	0.23
Diligence share	6,068	0.60	0.50	0.60	0.71	0.22
Risk/Approval share	6,068	0.40	0.25	0.43	0.53	0.24
Sourcing experience	6,068	5.21	3.00	4.78	6.71	3.67
Diligence experience	6,068	4.55	2.64	4.10	5.74	3.51
Risk/Approval experience	6,068	3.13	1.28	2.86	4.30	2.81
PE fund size share	6,068	0.00	0.00	0.00	0.00	0.00
Log firm age	6,068	1.50	1.10	1.61	2.08	0.70
Log classified employees	6,068	3.59	1.95	3.30	4.82	2.10

Notes: Sample covers 2014–2023. Restricted to firm-years with at least one function-classified employee. Function shares use the number of classified employees as the denominator. Experience variables are normalised by the number of classified employees (experience per classified employee). PE fund size share is the ratio of PE fund size to total fund size. Log firm age is the log of years since the firm first appears in the sample. Log classified employees is $\ln(\text{classified employees} + 1)$.

2.2 Contract customization

Most of the private credit financing is extended to middle-market firms that are not publicly traded[5]. We rely on a proprietary database from an anonymous third-party appraisal firm commonly used by private credit providers.[6] A key advantage of our data is that we observe the actual credit agreements for all loans held by private credit lenders, i.e., those originated by both banks and private credit firms.[7] This allows us to examine loan terms of both bank and non-bank contracts in detail.

Our final sample contains 2,347 credit agreements (761 "bank-originated" and 1,586 "PC-originated"), primarily issued to middle market borrower firms between 2014 and 2023. For each of these credit agreements, we are able to observe the complete underlying contract. From these contracts, we extract (i) basic deal terms, e.g., closing date, borrower identity, facility types, (ii) covenant packages and definitions, e.g., financial covenant thresholds, EBITDA definitions, negative covenant definitions, and (iii) other contractual provisions relevant to monitoring and enforcement of contract terms. We then standardize the extracted text and clause-level features across agreements so that contracts are comparable despite heterogeneous drafting styles and formatting. This structured contract dataset is the backbone for our measures of customization at both the extensive margin (whether nonstandard language/provisions are present), and the intensive margin (how far the language deviates from common boilerplate).

Panel B of Table 1 presents summary statistics for financial contracts originated by banks and those originated by non-banks.[8] The table reports borrower financial characteristics at the time of financing, including total assets (in USD millions), liquidity ($cash/assets$), leverage ($debt/assets$), tangibility (net $PP\&E/assets$), and profitability ($EBITDA/assets$), as well as an indicator for junior loans. The average bank in our sample is larger in size, having total assets of \$1.1 bn., than an average private credit firm having total assets of \$357 mn. The average debt to asset ratio for the non-bank in our sample is 59.3%, while the average debt to asset ratio for a bank is 66%. EBITDA to assets for an average non-bank the bank is also similar—19.8% for non-banks and 18.4% for banks.

We also report lender firm-level human capital measures, constructed at the time of loan origination, as additional summary statistics for our contract-level sample in Appendix B Table B1. The patterns are consistent with those in the full Revelio–PitchBook sample (Table 1). nonbank allocate a larger share of classified employees to diligence roles (66.1% vs. 60.8% at banks), while banks devote a higher share to

[5] Block et al. (2024) and Jang et al. (2025) report that 75-80% of private credit borrowers are private equity-backed.

[6] Jang (2025) and Jang and Kim (2025) show that the private credit loans in this sample are representative of those reported in PitchBook, a widely used commercial database for private credit deals (Haque et al., 2025).

[7] Haque et al. (2025) show that a large fraction of private credit deals are syndicated by banks.

[8] Table B1 in the Appendix reports the full set of loan-level statistics separately for PC-originated and bank-originated loans.

sourcing (64.1% vs. 53.1%) and risk/approval (45.9% vs. 30.9%).

Finally, it reports all previously defined measures of monitoring intensity and contract customization.

3 Stylized facts

3.1 Human capital differences across lenders

As a first step, we show the distribution of functions in non-banks and banks over time, as a percentage of employees whose job descriptions can be classified in at least one of the functions. Figure 2 Panel A shows that non-banks have a larger share of diligence roles compared to banks, while banks have a larger share of sourcing and risk/approval roles. These differences are stable over the sample period, suggesting persistent organizational differences in how the two lender types allocate human capital across intermediation functions. Panel B complements these patterns by plotting the average function-specific experience per classified employee over time. Experience levels trend upward for both groups across all three functions, consistent with the growing tenure of workers in our sample. Banks accumulate more sourcing and risk/approval experience per classified employee than non-banks, while non-banks build a comparative advantage in diligence experience—mirroring the compositional differences documented in Panel A.

Table 2 examines these differences more formally, regressing functional role shares (Panel A) and functional experience (Panel B) on a bank indicator for the 2014–2023 period. In Panel A, we define the presence of functional shares as the percentage of employees in each function, i.e., sourcing, due diligence, and risk approval, in a given firm year normalized by the number of employees which can be classified in any function in a given year. We find that private credit firms have significantly more individuals in diligence roles compared to banks. We control for the private equity fund size share as many private credit deals are financed jointly with private equity sponsors. We also control for the firm age and the number of employees which can be classified into a function to account for varying sizes at the lender level. The average share of classified employees in diligence roles is 61.8%. A coefficient of 8% implies that private credit firms have 12.9% more diligence roles compared to the average in the sample. On the other hand, we observe that banks have 17.3% more sourcing roles than the average 61.2% classified sourcing roles, and 16.8% more risk approval roles than the average 38.1% in the sample.

Panel B shows the presence of total years of functional experience per classified employee at the firm

Table 2: Presence of functions and experience across banks and non-banks - firm level

Panel A: Function Shares

	Sourcing		Diligence		Risk/Approval	
Non-bank (PC)	-0.103***	-0.106***	0.069***	0.080***	-0.086***	-0.064***
	(0.018)	(0.025)	(0.016)	(0.022)	(0.016)	(0.022)
Year FE	✓	✓	✓	✓	✓	✓
Controls		✓		✓		✓
Observations	8172	8172	8172	8172	8172	8172
R squared	0.033	0.037	0.017	0.019	0.024	0.043
Mean dep. var.	0.612	0.612	0.618	0.618	0.381	0.381

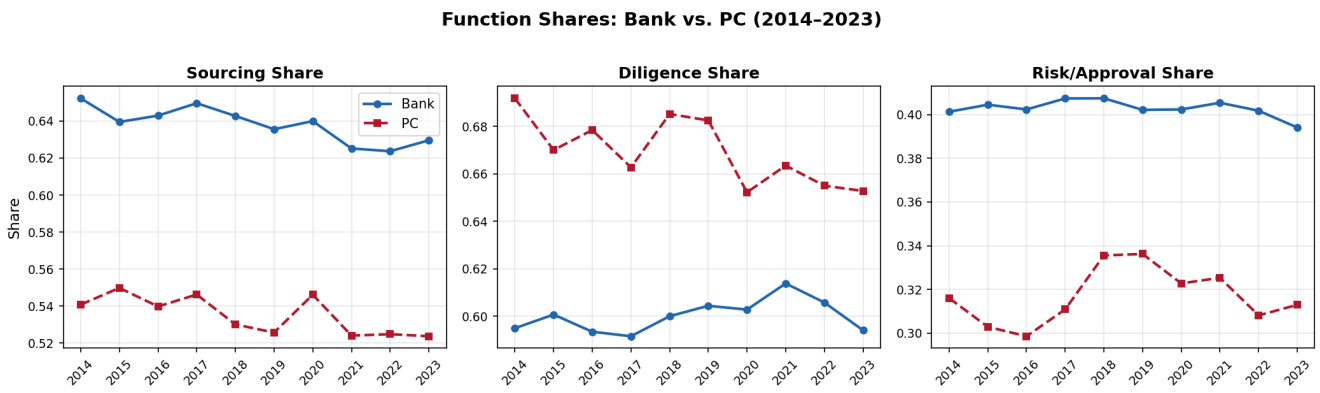
Panel B: Experience per Classified Employee

	Sourcing		Diligence		Risk/Approval	
Non-bank (PC)	-0.605**	-0.291	1.041***	1.401***	-0.757***	-0.394
	(0.242)	(0.344)	(0.280)	(0.380)	(0.185)	(0.273)
Year FE	✓	✓	✓	✓	✓	✓
Controls		✓		✓		✓
Observations	8172	8172	8172	8172	8172	8172
R squared	0.089	0.092	0.081	0.086	0.068	0.076
Mean dep. var.	5.060	5.060	4.826	4.826	2.938	2.938

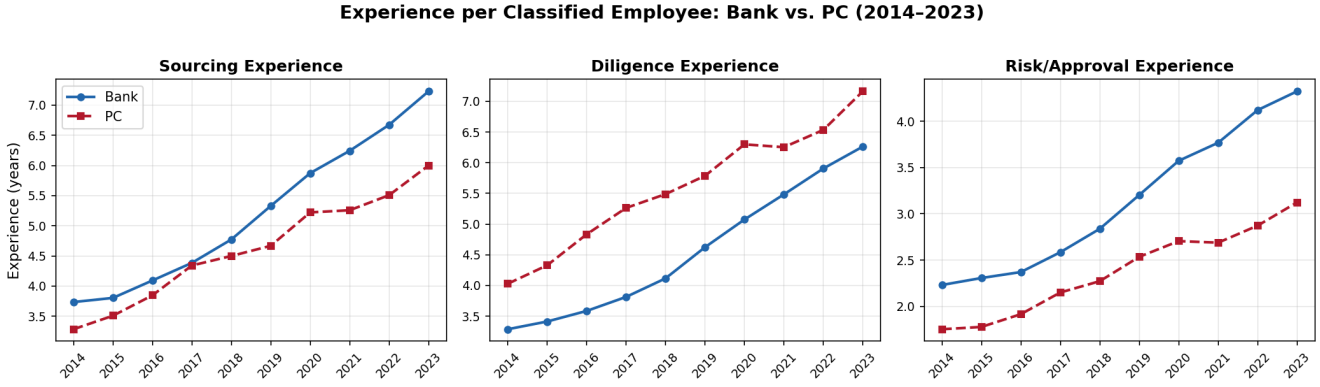
Standard errors in parentheses, clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1
Notes: This table compares the allocation and depth of lending-function human capital between PC firms and banks at the firm-year level. Panel A: The dependent variable is the percentage of employees in each function (sourcing, due diligence, or risk/approval) in a given firm year. We normalize the number of employees in each function by the number of employees available in any function in a given firm year. Panel B: The dependent variable is the total years of functional experience the employees in the firm-year possess divided by the number of classified employees in that firm-year. We consider the ultimate parent firm to define the firm. Controls include PE fund size share, log firm age, and log number of classified employees. Sample restricted to banks and PC firms.

Figure 2: Function Shares and Experience: Bank vs. Private Credit (2014–2023)

Panel A: Function Shares



Panel B: Experience per Classified Employee



Notes: Sample restricted to firm-years with `pcbankonly`=1 and at least one function-classified employee, 2014–2023 (2,104 PC and 6,068 bank firm-years). Panel A plots the yearly mean function share (number of employees in each function divided by total classified employees). Panel B plots the yearly mean experience per classified employee (average function-specific experience scaled by total employees over classified employees). Solid blue lines represent banks; dashed red lines represent private credit firms.

year level across banks and private credit firms. We include the same controls as Panel A to account for private equity share, the size of the firm, number of classified employees into a function in the firm, and year fixed effects. Private credit firms have a significantly higher diligence experience amongst their employees relative to banks. The average diligence experience per employee in the sample is 4.8 years. Private credit firms have 1.5 years more diligence experience per employee, which is 31.25% more relative to the average. Total years of sourcing and risk approval experience per classified employee is lower, but not statistically different in private credit firms as compared to banks. Table B2 includes both private equity and private credit firms in the non-bank sample and finds similar results. These results highlight the importance of diligence roles and experience in private credit firms relative to banks.

3.2 Contract customization differences across lenders

In this section, we construct contract customization measures at the contract level for bank and non-bank credit agreements over time. A typical credit agreement defines a set of contractual terms that can be extensively customized. In our sample, an average contract has 273 terms from 2014 to 2023, varying from 227 in 2014 to 299 to 2023.

Figure 3 Panel A shows the average total number of contractual terms used in bank- and PC-originated credit agreements. We find that PC-originated credit agreements rely on fewer terms on average than bank-originated credit agreements. However, the sheer number of terms does not necessarily indicate greater customization, as many included terms may be boilerplate.

To address this, we construct an extensive-margin measure of contractual customization. We define a novelty measure in term choice, which captures how non-standard a contract's terms are, following Murfin and Sun (2025). This measure is based on two components: (i) the proportion of 80 predefined boilerplate terms that appear across all contracts, and (ii) the proportion of contractual terms in a given contract drawn from these boilerplate definitions. A higher value of the first component indicates greater use of standard boilerplate language across contracts, while a higher value of the second indicates greater reliance on boilerplate terms within a specific contract. We compute the novelty measure as the equal-weighted average of these two components and subtract it from 1, so that higher values correspond to more novel, customized term choices. We show in Panel B that PC-originated loans include more novel terms in their credit agreements compared to bank-originated loans. Hence, despite the fact that private credit lenders include fewer terms, they appear to include more novel terms.

We also create an intensive margin measure of customization. We extend on the methodologies adopted in Murfin and Sun (2025), calculating the cosine similarity scores at the contract-year level relative to a boilerplate contract for banks and private credit lenders for each year based on the term definitions in the contracts. Figure 3 Panel C shows the average similarity scores for credit agreements by banks and non-banks over time. The average and median cosine similarity score is increasing for all contracts over time, indicating that as more contracts are being signed, lenders might be learning from other contracts and writing similar contracts.

Notably, we observe a clear difference in the levels of similarity between credit agreements originated by private credit lenders and banks. PC-originated loans show an average similarity score of 45% between 2014 and 2023, while the bank contracts depict an average similarity score of 55% over the same time period. This shows that non-bank credit agreements are more customized relative to their boiler

plate.

Beyond individual contractual terms, borrowers and lenders often negotiate over control rights through a variety of covenants. Prior literature has focused primarily on the incidence of financial (i.e., maintenance) covenants (e.g., Chava and Roberts (2008); Roberts and Sufi (2009); Nini et al. (2012)) or on the number of "permitted exceptions" (also known as baskets) (e.g., Ivashina and Vallée (2025)).

We build on existing measurement to capture the customization of contractual terms for both financial and negative covenants. For financial covenants, it is common for credit agreements to include a debt-to-EBITDA covenant or an interest coverage covenant; however, the definition of EBITDA is often intensely negotiated.[9] Using the same methodology as before, we measure the distance of EBITDA definitions from the boilerplate. As shown in Panel D, this distance, on average, is higher for PC-originated loans.

Unlike financial covenants, negative covenants specify ex-ante a set of actions that the borrower is prohibited from undertaking, and the definitions of these baskets can also be highly customized. Similar to the EBITDA definition, we measure the distance of contractual definitions of negative covenant baskets from the boilerplate for six common types: restrictions on liens, indebtedness, investments, restricted payments, asset sales, and fundamental changes. Panel E shows that the average distance for negative covenants has generally been higher for PC-originated loans, driven primarily by indebtedness, investments, and restricted payments (Appendix Figure A5), although there was a reversal in 2023.

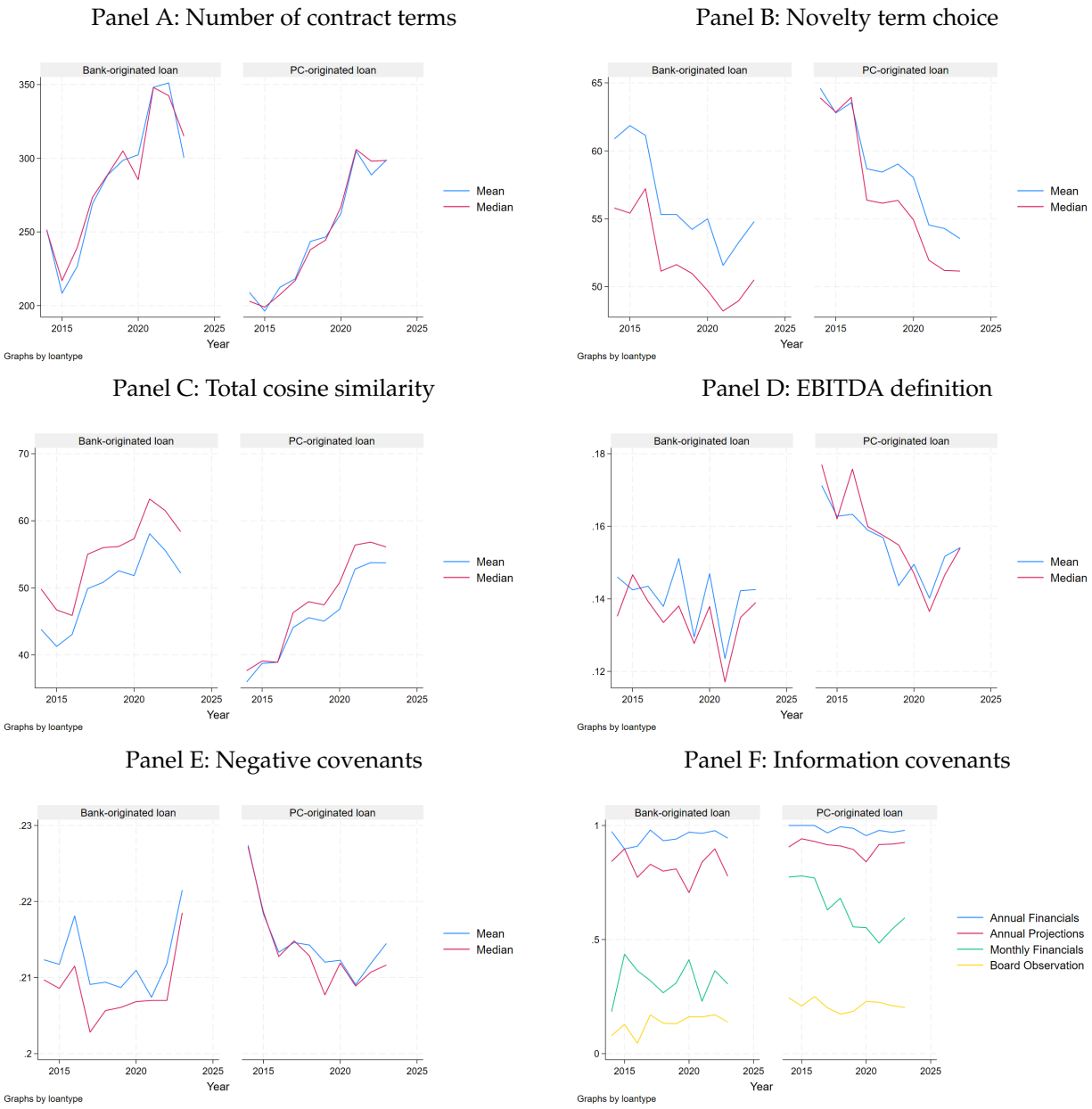
Finally, also new to the literature, we conduct a detailed examination of information covenants. Beyond the nearly universal requirement of annual financial statements, lenders can impose more intensive monitoring, including cash flow projections, higher-frequency financial reporting, and board observation rights. Panel F shows that private credit lenders more frequently require monthly financials and board observation rights. This suggests that private credit lenders monitor more stringently than banks, which are traditionally known to be good monitors, along the information dimension, possibly because of the inherent relatively riskier nature of the borrowers financed by private credit firms.

Taken together, these results suggest that, private credit lenders tend to customize contractual terms more than banks, both on extensive and intensive margin. They are also more actively involved in customizing the definitions of EBITDA, a key input for most financial covenants, as well as negative

[9]Financial covenants act as periodic "tripwires" that creditors use to detect declines in firm performance. When these covenants are breached, creditors respond by intensifying monitoring and exercising greater control over the firm's activities, consistent with the theory of state-contingent control (Aghion and Bolton, 1992).

covenants that restrict borrower activities. However, these differences are unconditional and do not account for differences in borrower characteristics. Moreover, it remains unclear whether differences in human capital can explain the observed patterns. We investigate these questions in Section 4.

Figure 3: Similarity measures for bank and non-bank contracts over time



Notes: This figure compares various measures of contractual customization between PC-originated and bank-originated loans. Panels A-E show the mean and median number of contract terms, novelty term choice, total cosine similarity, EBITDA distance from boilerplate, and negative covenant distance from boilerplate. Panel F reports the average fraction of loans requiring annual financials, annual projections, monthly financials, and board observation rights.

4 Connecting lender type, contract customization, and human capital

In this section, we examine the empirical relationships between the contractual customization measures, lender type (i.e. private credit versus bank), and the lenders' underlying human capital measures.

Our main specification follows the following functional form:

$$y_{i,j,t} = \alpha + \beta_1 \mathbb{I}_{PC_j} + \beta_2 H_{j,t} + \beta_3 (\mathbb{I}_{PC_j} \times H_{j,t}) + \beta_4 \Gamma_{i,t} + FEs + \epsilon_{i,j,t} \quad (1)$$

where $H_{j,t}$ denotes a measure of human capital of lender j in year t, $\mathbb{I}_{PC_j}$ is an indicator for the lender j being a PC lender (0 if a bank), $y_{i,j,t}$ takes one of the six measures of contractual customization from Section 3.2 — similarity, novelty, EBITDA distance, negative covenant distance, a requirement of monthly financials, and board observation right — for the loan between borrower firm i and lender j in year t. As controls ($\Gamma_{i,t}$), we include a set of time-varying borrower characteristics (size, liquidity, leverage, tangibility, and profitability), as well as an indicator for whether the loan is junior. These controls are intended to capture heterogeneity in firm demand, as different types of borrowers may sort into different types of lenders (Chernenko et al., 2022; Jang, 2025). We also include industry, deal type and year fixed effects, and the standard errors are double-clustered by lender and year.

We implement these regressions to investigate four empirical questions. First, do PC-originated loans exhibit greater contractual customization even after controlling for observable characteristics? We examine this by estimating β_1 when $\mathbb{I}_{PC_j}$ is the main explanatory variable. Second, are the human capital measures associated with contractual customization? This relationship is reflected in β_2 when $H_{j,t}$ is the main explanatory variable. Third, does a specific type of human capital matter more for one type of lender than the other? This will be captured by β_3 on the interaction term. Finally, if human capital is indeed an important determinant of contract innovation, can differences in human capital between private credit lenders and banks explain the observed differences in contractual customization? We assess this by estimating β_1 in specifications that also include the other explanatory variables.

Table 3 reports the estimation results using lender due diligence share as the primary measure of human capital. Diligence roles combine screening, underwriting, and monitoring activities, hence the diligence share is most likely to capture a lender's human capital emphasis on the analytical skills required to understand a borrower's business and, in turn, to design more customized contractual terms. In fact, Appendix Table B3 shows that the other human capital measures (sourcing and risk-approval) either have no effect or are negatively and statistically significantly associated with the customization

measures. This makes sense intuitively as sourcing roles are associated with tapping into client relationships, and risk and approval roles are centered around assessing portfolio risks or risk management. This reinforces our approach of measuring human capital functions separately.

As shown in Columns (1) and (4) of all three panels, the PC indicator is positively associated with all six measures of contractual customization (for the similarity measure, a lower value indicates greater customization). With the exception of negative covenant distance, the estimated coefficients are statistically significant at the 5% level or higher. In fact, when we examine covenant distance separately by type (see Table B4 in the Appendix), we find that the largest differences arise for those tied to the three core pillars of corporate finance: financing (indebtedness), investment, and payout (restricted payments). These findings suggest that the unconditional differences in customization between PC-originated and bank-originated loans remain statistically significant even after controlling for time-varying borrower characteristics, as well as industry, deal type, and year fixed effects.

Interpreting the magnitudes, the differences in Novelty, Similarity, EBITDA Distance, and negative covenant distance are 15%, 17%, 18%, and 10% of their respective standard deviations. For the monitoring terms, the differences are relatively larger, at 16% and 7%, compared with mean frequencies of 50% and 19%, respectively. Even though the individual effect sizes are modest, when considered together across all six measures, which all point in the same direction, these results suggest that PC-originated loans exhibit broadly greater contractual customization than bank-originated loans.

Turning to Columns (2) and (5) across panels, we find that lender due diligence share of human capital is positively associated with three contract customization measures (similarity, EBITDA distance, and the requirement of monthly financial statements) at the 5% significance level, and with negative covenant distance at the 10% level. These results are consistent with the view that a lender's emphasis on due diligence–related human capital facilitates the design of more customized contracts.

Finally, Columns (3) and (6) across panels show that, once we interact lender due diligence share with an indicator for PC-originated loans, the estimated coefficients on the interaction term ($\mathbb{I}_{PC_j} \times H_{j,t}$) are positive and statistically significant for novelty (10%), similarity (5%), negative covenant distance (5%), and monthly financials (1%). This suggests that private credit lenders' emphasis on due diligence–related human capital has a stronger effect on contract customization. Interestingly, the estimated individual effects of due diligence share are negative and significant for monthly financials and board observation, suggesting that banks' higher focus on due diligence human capital is actually associated with less reliance on monitoring. One possible interpretation is that banks with stronger due diligence

Table 3: Role of Due Diligence Human Capital

Panel A: Term Customization

	Novelty			Similarity		
	(1)	(2)	(3)	(4)	(5)	(6)
PC	1.871***		-8.709	-2.857***		15.193*
	(0.665)		(5.808)	(0.906)		(8.257)
Diligence Share		3.776	-13.052		-8.355**	19.839
		(2.622)	(8.979)		(3.529)	(12.838)
PC X Diligence Share			17.163*			-29.095**
			(9.322)			(13.252)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Deal type FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2314	2314	2314	2304	2304	2304
R-squared	0.12	0.11	0.12	0.17	0.17	0.18

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Covenant Customization

	EBITDA Distance			Neg. Cov. Distance		
	(1)	(2)	(3)	(4)	(5)	(6)
PC	0.007***		-0.004	0.002*		-0.014*
	(0.002)		(0.018)	(0.001)		(0.008)
Diligence Share		0.023**	0.003		0.008*	-0.017
		(0.009)	(0.028)		(0.004)	(0.012)
PC X Diligence Share			0.017			0.025**
			(0.030)			(0.013)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Deal type FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2042	2042	2042	2049	2049	2049
R-squared	0.16	0.16	0.17	0.07	0.06	0.07

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel C: Monitoring

	Monthly Financials			Board Observation		
	(1)	(2)	(3)	(4)	(5)	(6)
PC	0.159***		-0.543***	0.072***		-0.154
	(0.028)		(0.177)	(0.018)		(0.154)
Diligence Share		0.239**	-0.907***		-0.107	-0.512**
		(0.095)	(0.265)		(0.091)	(0.230)
PC X Diligence Share			1.142***			0.383
			(0.290)			(0.253)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Deal type FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2314	2314	2314	2314	2314	2314
R-squared	0.25	0.23	0.26	0.05	0.04	0.05

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable takes a measure of contractual customization. Panel A reports results for similarity and novelty; Panel B reports results for EBITDA distance and negative covenant distance; and Panel C reports results for the requirement of monthly financial statements and board observation rights. The main explanatory variables are an indicator equal to one for a PC-originated loan (and zero if bank-originated), lender due diligence human capital share, and their interaction. As controls ($\Gamma_{i,t}$), we include a set of time-varying borrower characteristics (size, liquidity, leverage, tangibility, and profitability), as well as an indicator for whether the loan is junior. We include industry, deal type, and year fixed effects, and standard errors are double-clustered at the lender and year levels.

skills are better able to screen out riskier borrowers ex-ante, thereby reducing the need for ex-post monitoring, though this remains speculative.

Importantly, the signs on the estimated coefficients for $\mathbb{I}_{PC_j}$ now reverse, with some of the flipped coefficients statistically significant. This suggests that the apparent advantage of private credit lenders in contract customization largely reflects their human capital. In fact, without these differences, the results imply that private credit lenders might customize less. One way to interpret this is to imagine private credit lenders and banks stripped of human capital, leaving only organizational capital. In that scenario, private credit lenders would likely perform worse, which makes sense given that private credit firms are relatively new, while banks have had more time to build organizational capital supporting their lending technology.

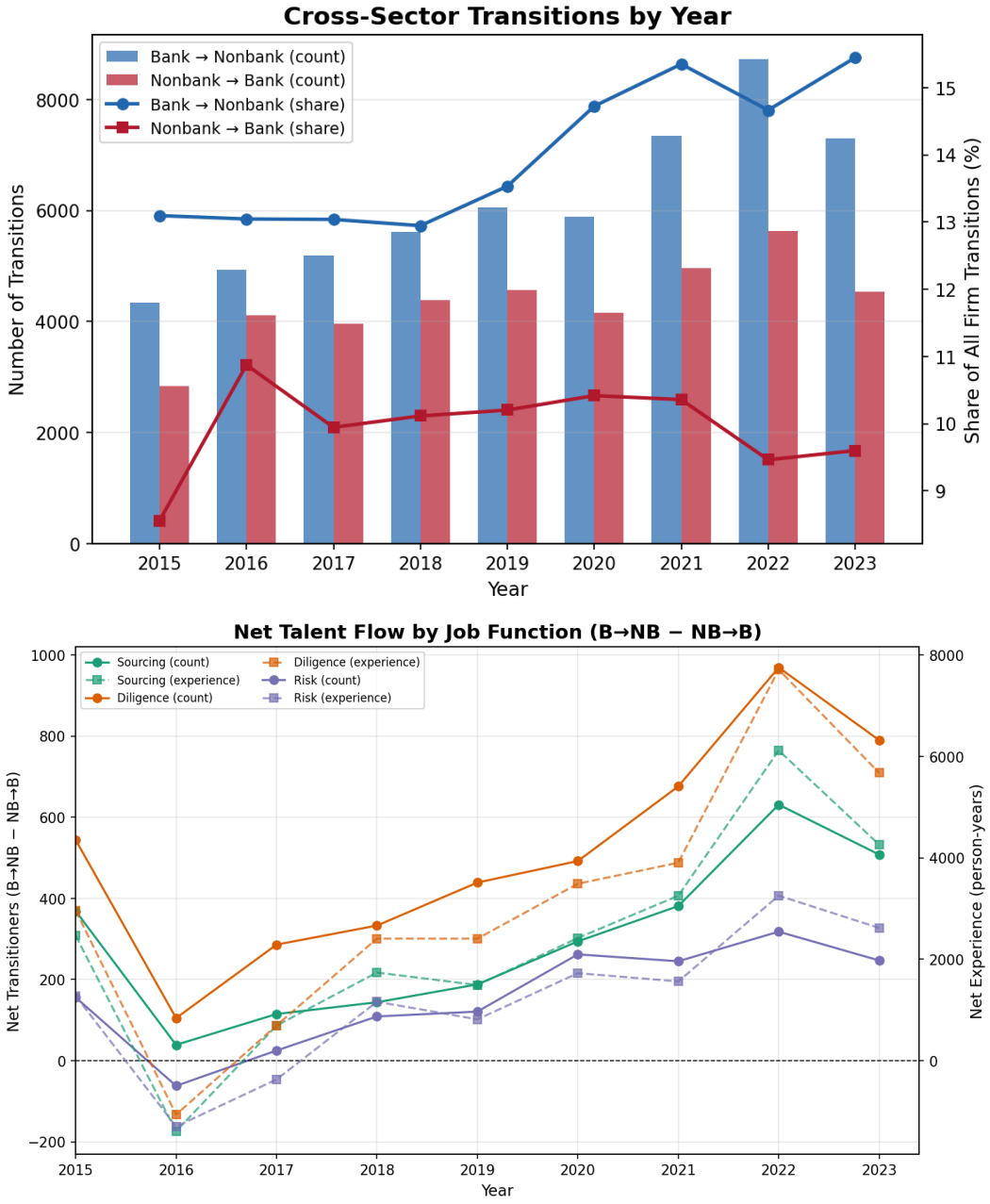
5 Implications for career mobility, seniority, and compensation

In the above sections, we have shown that the presence of diligence human capital in private credit firms is associated with greater customization and monitoring contractual terms in these lender firms relative to banks. In this section, we investigate the past experience of the diligence human capital in private credit firms, and its implications for the seniority and compensation in their roles.

We observe substantial labor mobility between banks and non-banks. Figure 4 Panel A shows that movement of employees from banks to non-banks is much higher, at 13.6% of all firm transitions in 2023 than movement of employees from non-banks to banks, which is at 8.5% of all firm transitions at 2023. This suggests that individuals get experience from banks before moving to private equity and private credit roles. Figure B1 documents the consistent net outflow of human capital from banks to non-banks. The figure shows number of job transitions and number of years of transition for each person-year calculated by subtracting non-bank to bank transitions from bank to non-bank transitions. The positive uptrend over the years shows a growing number of transitions out of the banking sector. Figure 4 Panel B documents the net outflow of jobs from banks to non-banks by functional roles. We find that while the net outflow has been consistent across functions, the diligence roles at non-banks have been increasingly sourced by banks, both in terms of number of transitions and the years of experience being transitioned. Employees are banks are spending longer time at banks in due diligence roles before transitioning to non-banks as compared to sourcing and risk-approval roles.

Table 4 shows the seniority of the title, salary, and total compensation of individuals transitioning

Figure 4: Distribution of roles in banks and non-banks



Notes: This figure shows transitions of roles between banks and non-banks by year. Panel A shows number of job transitions from banks to non-banks and non-banks to banks in each year from 2015 to 2023 (left axis). Panel A also shows the percentage of job transitions from banks to non-banks and non-banks to banks separately, as a share of all firm transitions from 2015 to 2023 (right axis). Panel B shows the net outflows of job transitions (solid lines) and experience years (dotted lines) by function: sourcing, diligence, and risk approval from 2015 to 2023. Data are sourced from Revelio.

from banks to diligence roles in private credit firms. Panel A shows how seniority and compensation for the private credit employee correlate with the presence of diligence experience at the prior bank, and Panel B shows the correlation with the total years of diligence experience at the prior bank relative to the other functions. The diligence employee in the private credit firm will receive a more senior role by 9.4% relative to the average 3.1 seniority level if the employee had a prior diligence experience at the bank

relative to any other functional experience. The employee will also receive an annual total compensation which is 9.5% higher than the average $155,311 if they enter the diligence role at the private credit firm with a prior diligence experience at the bank. Panel B shows that years of prior diligence experience at banks also plays a crucial role for career progression and compensation. An additional year of prior bank diligence experience, increases seniority by 3.2% and total compensation by 4.1% relative to the average for the private credit employee in a diligence role. These results are statistically significant at 1% level.

While prior experience raises the probability of upward career mobility and compensation raise, we also suggest that diligence roles play a key role in this trajectory. Tables B5 and B6 study individuals transitioning from banks to sourcing and risk/approval roles in private credit firms, respectively. For sourcing roles in private credit firms, we find that presence of a prior sourcing experience in banks does play a key role in senior mobility but the years of sourcing experience is of less importance in terms of economic magnitude. The coefficient on total compensation though positive is not statistically significant (Panel A, Table B5). For risk/approval private credit roles, the economic magnitudes on prior bank risk/approval experience are positive but less when compared to the diligence case. The coefficient on total compensation is negative and not statistically significant (Panel A, Table B6). These results suggest that prior diligence experience in banks plays a more important role for diligence roles in private credit firms, than for the cases of sourcing and risk approval transitions. A possible reason is that contract underwriting, monitoring, and screening technologies are valuable skills which an employee learns from their prior bank experience, especially given the traditional advantage of banks in these domains. Given the recent rise of non-bank financing, prior diligence skills are portable and valuable in private credit financing which are needed for contract customization. These skills are rewarded with seniority in titles and compensation.

6 Conclusion

This paper shows the importance of human capital in financial contracting across lender types. Using novel data on job descriptions of individuals employed at banks and private credit firms, we find that banks have had consistently more employees in sourcing and risk/approval roles, while private credit firms have more employees in diligence roles. Using state-of-the-art NLP techniques on individual credit agreements of banks and private credit lenders, we find that private credit firms write more

Table 4: Diligence transitioners: seniority and compensation

Panel A: Indicator

	Seniority		Salary		Total Comp.	
Diligence Experience at Banks	0.290***	0.292***	9125.531***	9300.828***	14363.440***	14629.646***
	(0.041)	(0.041)	(2436.884)	(2345.675)	(4201.673)	(4130.254)
Year FE	✓	✓	✓	✓	✓	✓
Controls		✓		✓		✓
Observations	7094	7094	7092	7092	7092	7092
R squared	0.009	0.035	0.031	0.056	0.014	0.031
Mean dep. var.	3.108	3.108	113897.666	113897.666	155311.433	155311.433

Panel B: Years of Experience

	Seniority		Salary		Total Comp.	
Diligence Experience at Banks (Years)	0.101***	0.099***	3548.580***	3495.913***	6513.829***	6393.544***
	(0.007)	(0.006)	(410.681)	(395.150)	(741.907)	(720.792)
Year FE	✓	✓	✓	✓	✓	✓
Controls		✓		✓		✓
Observations	7094	7094	7092	7092	7092	7092
R squared	0.069	0.092	0.064	0.088	0.044	0.060
Mean dep. var.	3.108	3.108	113897.666	113897.666	155311.433	155311.433

Standard errors in parentheses, clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1
Notes: This table examines whether prior bank diligence experience predicts seniority and compensation for individuals who transition from banks to nonbanks and work in diligence roles. Sample consists of bank-to-nonbank transitioners (individuals at a bank in year $t-1$ and at a nonbank in year t), restricted to those who had a job description while at the bank and are currently in a diligence function (screening, underwriting, or monitoring) at the nonbank. Panel A: the regressor is an indicator for having any prior diligence experience at a bank; the control group consists of individuals in any other lending function at banks. Panel B: the regressor is years of prior diligence experience at a bank; the control group is experience in any other lending function. Controls include indicators for MBA, graduate degree, gender, and race/ethnicity. We consider the ultimate parent firm to define the firm.

customized and novel contracts than banks. Connecting the human capital measures with contract customization, we find that diligence human capital at private credit firms play a key role in explaining customization of contracts. These results suggest that diligence human capital, capturing monitoring and underwriting functions, are key to the private credit industry which is primarily financing private borrowers with limited public information.

Our paper sheds light on the monitoring advantages in the private credit industry relative to banks, which have historically been known for these functions. We further study the implications for career trajectories of individuals employed in diligence roles at private credit firms. We find substantial net outflow of individuals from bank diligence roles to private credit diligence roles. These individuals are rewarded with higher job seniority and total compensation. Our work has important implications for employees and financial contracting in the bank and non-bank industry.

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Appendix

A Data Appendix

A.1 Data Construction

A.1.1 Credit agreements from a financial advisory firm

We obtain our sample of credit agreements from an anonymous third-party appraisal firm specializing in private capital valuations, previously used by Jang (2025); Jang and Kim (2025), who demonstrate its representativeness of private credit deals. The sample covers 2,347 agreements, including both bank-originated and PC-originated loans from 2014 to 2023.

A.1.2 Individual job histories from LinkedIn, Revelio Labs

Our job history data comes from Revelio Labs, a workforce intelligence provider that aggregates and standardizes publicly available professional profiles from online platforms, primarily LinkedIn. The dataset provides comprehensive employment timelines for millions of individuals, including standardized job titles, employer names, start and end dates, location, and educational background.

From this universe, we construct a panel of employment histories for individuals working in the finance industry. We then restrict the sample to employees of the lenders identified in Section A.1.3. To link lenders to Revelio, we query positions using each lender's `ultimate_parent_rcid`, which is Revelio's parent-level firm identifier that maps all subsidiary entities to a single ultimate parent. This approach captures all employees across the organizational hierarchy of each lender, including those at subsidiary entities that may operate under different names (e.g., subsidiary funds, regional offices, or specialized lending vehicles). We restrict positions to those located in the United States and apply role-based filters to retain employees in lending-relevant functions (e.g., origination, credit analysis, portfolio management), excluding non-core roles such as IT, marketing, and human resources.

A.1.3 Defining the intermediaries from Pitchbook

A key challenge in studying officer human capital in private credit is defining a consistent set of intermediaries (lenders/arrangers). We rely on Pitchbook to construct the universe of private-credit intermediaries and to scope our analysis to the set of institutions that are active in private lending during our sample period. We use this intermediary list to (i) restrict the set of lenders we track in the officer

data, (ii) harmonize naming and identifiers across sources, and (iii) limit the contract sample to deals involving intermediaries in our defined universe.

A.1.4 Linking Revelio, Contracts, and Pitchbook

To merge human capital information to contract-level customization measures, we first construct a crosswalk between Revelio Labs and Pitchbook using a hierarchical matching procedure. We attempt matches on: (1) LinkedIn company URLs, (2) website URLs, (3) SEC CIK codes, (4) legal company name combined with headquarters location (city, country, zip code), (5) cleaned company name with headquarters location, and (6) phone numbers. When multiple methods produce valid matches, we prioritize more unique identifiers (LinkedIn and website URLs) over name-based matching. The Revelio data is restricted to financial sector firms (NAICS 52).

We then construct a crosswalk between Pitchbook and lead lenders from our proprietary loan-level data by manually matching lead lender names to Pitchbook entities. Together, these two linkages allow us to trace human capital measures from Revelio through Pitchbook to the contract-level data, enabling us to relate lender workforce characteristics to loan customization outcomes.

A.1.5 Final sample and unit of observation

Our baseline unit of observation is the *contract–intermediary* (and, when officer assignment is observed, the *contract–officer*) level. We impose standard sample restrictions to ensure that (i) the agreement text is available and parsable, (ii) the lender/intermediary can be mapped to our intermediary universe, and (iii) officer histories provide sufficient pre-contract information to construct human-capital measures. We report summary statistics and coverage diagnostics (contracts, intermediaries, officers, and years) in Section 2.

A.2 Classification of individual roles at intermediaries

Our unit of analysis is individual positions at lending intermediaries. We start from the universe of Revelio Labs employment records matched to PitchBook intermediaries and apply two sequential filters to arrive at the set of intermediation-specific roles used in our analysis. We perform this step because we only want to focus on human capital related to financial intermediation. For instance, we don't want to include any bank employees associated with deposit-taking activities, compliance or legal/accounting functions.

We first restrict the sample to U.S.-based positions and remove roles that are clearly unrelated to lending or investment activity. Using job titles and Revelio's occupation taxonomy (role_k1500 and role_k17000), we exclude: (i) external consultants and contractors (retaining financial and investment consultants); (ii) consumer and retail banking positions (e.g., tellers, branch managers, mortgage officers, wealth advisors); (iii) marketing and telemarketing; (iv) human resources and recruiting; (v) information technology and software engineering (retaining financial engineers and structuring roles); (vi) tax and accounting (retaining fund accountants); (vii) administrative support (retaining fund, trust, and loan administrators); (viii) general operations (retaining loan, investment, trading, credit, and portfolio operations); and (ix) other non-core roles (e.g., customer service, interns). Matching is performed on the concatenation of all available title and role fields, with spaces removed to capture compound titles.

A.2.1 Classification of roles into functions

In the second step, we classify each remaining position into six intermediation functions based on keyword stems appearing in the job description text. The functions, motivated by the stages of the lending process, are:

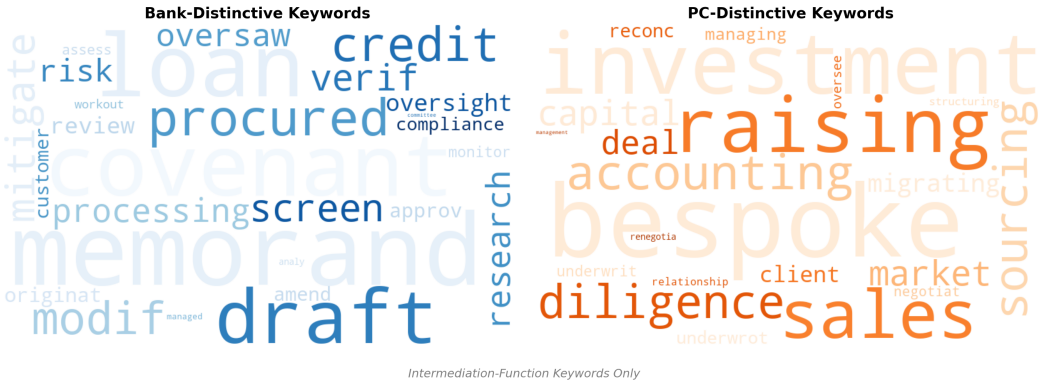
- *Sourcing*: deal origination, client relationship management, and capital raising (e.g., "originat," "relationship," "sourcing," "sales," "capital raising");
- *Screening*: initial evaluation and due diligence (e.g., "screen," "diligence," "analy," "research");
- *Underwriting*: credit structuring and documentation (e.g., "underwrit," "structuring," "negotiat," "memorand," "draft," "bespoke");
- *Approval*: credit committee review and compliance (e.g., "committee," "approv," "compliance," "verif," "reconc");
- *Risk management*: portfolio risk assessment (e.g., "risk assess," "mitigate risk," "risk management");
- *Monitoring*: ongoing loan surveillance and workouts (e.g., "covenant," "modif," "workout," "amend," "renegotia," "oversight").

All keyword matching uses case-insensitive substring logic (e.g., "underwrit" matches underwriting, underwritten, and underwrite). Function categories are not mutually exclusive: a single position may

be classified under multiple functions. We define a position as having an intermediation role if its description contains at least one keyword from any of the six categories (func_any $= 1$). Positions that pass the role filter in Step 1 but contain no intermediation keywords are excluded from our main analyses.

For parsimony in our regression analyses, we aggregate the six narrow functions into three broad categories that correspond to distinct stages of the intermediation process. *Sourcing* retains the narrow sourcing classification (func_source). *Diligence* combines screening, underwriting, and monitoring—the functions involved in evaluating, structuring, and tracking credit exposures (func_screen ∪ func_underwrite ∪ func_monitor). *Risk/Approval* combines risk management and approval—the functions responsible for independent risk assessment and credit committee decisions (func_risk ∪ func_approve). A position is assigned to a broad function if it belongs to any of the constituent narrow functions. As with the narrow categories, the broad categories are not mutually exclusive.

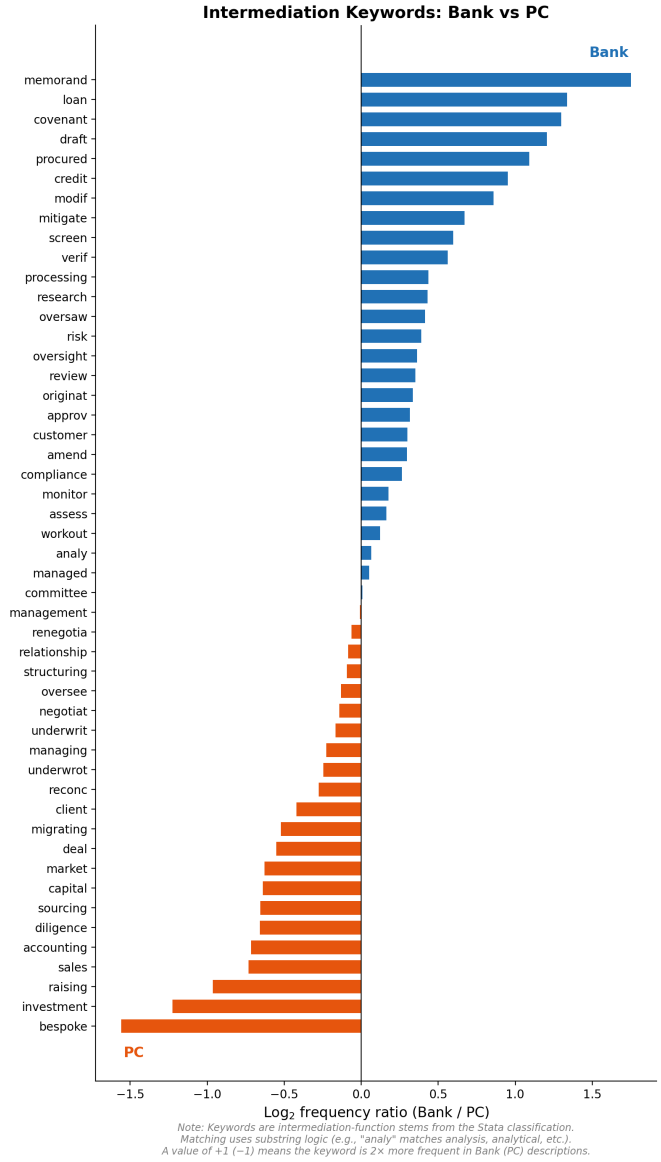
Figure A1: Word Cloud (Differential Keywords Only)



Notes: This figure displays differential word clouds comparing intermediation-function keywords in job descriptions of bank versus nonbank. Word size reflects the degree of overrepresentation (log frequency ratio) in that lender type. The left panel (blue) shows bank-distinctive keywords; the right panel (orange) shows PC-distinctive keywords. Keywords are restricted to predefined intermediation-function stems spanning sourcing, screening, underwriting, approval, risk management, and monitoring. The sample is restricted to positions classified as having a lending intermediation function. Data are from Revelio job descriptions matched to PitchBook lenders.

Figures A1 and A2 illustrate how the relative intensity of these intermediation keywords differs across lender types. The word cloud sizes words by overrepresentation; the bar chart quantifies the same differences as $\log_2$ frequency ratios. Bank job descriptions disproportionately emphasize keywords associated with sourcing and risk management—memorand," loan," covenant," draft," procured," credit," and modif" are among the most bank-distinctive terms, each appearing at least twice as frequently in bank descriptions. Keywords related to risk oversight and monitoring, such as risk," oversaw," oversight," compliance," and screen," are likewise overrepresented at banks, consistent with structured, committee-based credit approval and ongoing covenant enforcement. By contrast, PC lender descrip-

Figure A2: Intermediation Keywords: Bank vs. PC (Log Frequency Ratio)



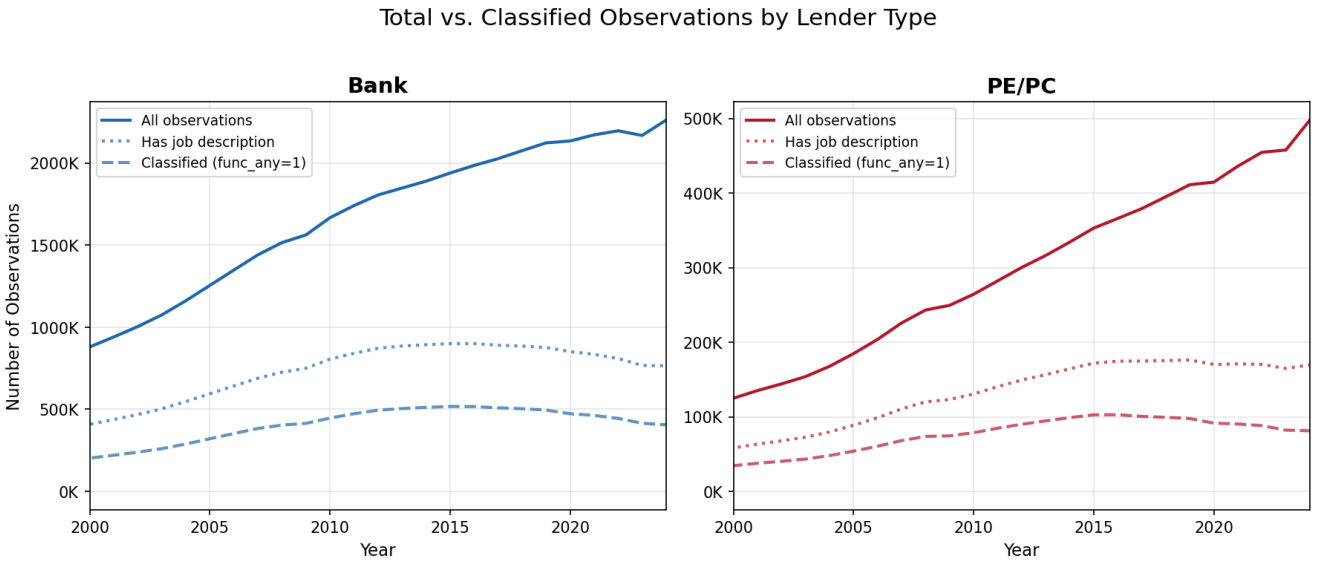
Notes: This figure plots the $\log_2$ frequency ratio (bank/PC) for each intermediation-function keyword stem. A value of $+1$ (-1) indicates the keyword is twice as frequent in bank (PC) job descriptions; $+2$ (-2) indicates four times as frequent. Blue bars denote bank-overrepresented keywords; orange bars denote PC-overrepresented keywords. Frequencies are normalized within each lender type. Keywords are intermediation-function stems used in the classification described in Appendix **??**; matching uses substring logic (e.g., "analy" matches analysis, analytical, etc.). The sample is restricted to positions classified as having a lending intermediation function. Data are from Revelio job descriptions matched to PitchBook lenders.

tions are dominated by diligence and deal-oriented keywords: bespoke," diligence," accounting," sourcing," investment," raising," and sales" all appear with $\log_2$ ratios below -0.5. The prominence of diligence," accounting," and renegotia" suggests that nonbank lending roles place greater emphasis on evaluating and structuring credit solutions for individual borrowers, while the overrepresentation of bespoke" and structuring" reflects the tailored nature of private credit transactions.

Figure A3 illustrates the effect of each filter on sample size, separately for banks (left panel) and

PE/PC lenders (right panel). The solid line plots the total number of person-firm-year observations at each lender type after the role-based exclusions described above. The dotted line restricts to observations whose underlying Revelio record contains a non-empty job description, which is required for keyword classification. The dashed line further restricts to observations classified as having an intermediation function (func_any = 1). For banks, total observations grow from roughly 900,000 in 2000 to over 2.2 million by the early 2020s, of which approximately 40% have job descriptions and roughly 20–25% are ultimately classified as intermediation roles. PE/PC lenders exhibit steeper growth—from under 100,000 observations in 2000 to nearly 500,000—with similar classification rates. The gap between the description and classified lines reflects positions that, while not excluded by the role filter, do not mention any intermediation-function keywords in their job descriptions (e.g., general investment professionals whose descriptions emphasize portfolio returns rather than lending activities). The decline in the description and classified series in the most recent years is consistent with right-censoring in Revelio's coverage of recent job postings.

Figure A3: Coverage of Revelio data by intermediary types



Notes: We plot the number of 1) total observations, 2) observations with job descriptions, and 3) number of observations with job descriptions classified into functions from 2000 to 2024, separately for banks, and private equity or credit firms.

A.2.2 Classification of roles into industries

In addition to intermediation functions, we classify each position by the *borrower industries* referenced in its job description. This captures the sector expertise embedded in a lender's workforce—for example, whether an analyst's description mentions healthcare, real estate, or technology clients—rather than the

lender's own industry. We define 14 industry categories using keyword-based substring matching on the job description text:

1. *Technology*: information technology, fintech, AI, blockchain, telecom, cleantech, etc.;
2. *Data/AI*: data science, AI (case-sensitive), machine learning platforms;
3. *Healthcare*: hospitals, pharmaceuticals, medical devices, life sciences, clinical trials, etc.;
4. *Media*: communications, digital media, telecom, TMT, social media, gaming;
5. *Industrial*: manufacturing, warehousing, wholesale, chemicals, minerals;
6. *Business services*: SaaS, education, hospitality, tourism, restaurants;
7. *Consumer*: consumer goods, food & beverage, auto lending, CPG, personal care;
8. *Retail*: retail, e-commerce, merchandise, malls, self-storage;
9. *Real estate*: CRE, CMBS/RMBS, mortgage, multi-family, REIT, infrastructure;
10. *Transportation*: trucking, aviation, aerospace, defense, marine, construction;
11. *Climate/Energy*: oil & gas, renewables, utilities, mining, carbon, environmental;
12. *Agriculture*: agribusiness, farming, irrigation, food security;
13. *Government*: national security, military, government agencies (USAID, DOJ, DOD);
14. *Financial institutions*: fixed income, CLOs, ABS, insurance, credit cards, digital finance.

As with the function categories, industry classifications use case-insensitive substring matching on the lowercased job description, with selected terms (e.g., "AI," "CLO," "ABS," "CRE," "SAAS") matched case-sensitively on the original text to avoid false positives. Industry categories are not mutually exclusive: a position whose description mentions both healthcare and technology clients is flagged under both. We construct an aggregate indicator, ind_any, equal to one if the position is classified under at least one industry.

A.3 Customization measures from credit agreements

To quantify the degree of customization and innovation at the contract level, we construct proxies along both extensive and intensive margins. The extensive margin captures the introduction of novel provisions, such as newly added definitions or covenants. The intensive margin measures the degree of variation and specific tailoring within existing terms. We rely specifically on the definitions and negative covenants sections to construct these measures. While these sections do not comprise the entire agreement, they represent the primary loci of contractual customization. Furthermore, prior literature demonstrates that the definitions section alone effectively serves as a sufficient statistic for contractual heterogeneity (Murfin and Sun, 2025).

A.3.1 Extraction of defined terms

To extract the set of defined terms from contracts, we build upon the methodology in Murfin and Sun (2025). For each credit agreement, we extract the Terms and Definitions (T&D) section – typically the opening section of the contract – using Python regular expression scripts. Focusing on this section is appropriate because terms defined here are referenced throughout the contract. For example, when EBITDA or Adjusted EBITDA is defined in the T&D section, subsequent financial covenants invoke that specific definition. Consequently, the T&D section serves as a sufficient statistic for overall contract customization, capturing economically meaningful variation while abstracting from boilerplate language in other sections.

We then identify and extract defined terms by exploiting consistent formatting conventions. Defined terms typically appear in quotation marks followed by phrases such as "means," "shall mean," or "is defined as." The quoted term, subject to manual standardization, becomes the definition label.

A.3.2 Identifying boilerplate terms

To measure contract novelty and customization, we construct annual boilerplate contracts that represent market-standard language. The boilerplate captures the median contractual structure in a given year, providing a benchmark against which individual contracts can be compared. This approach allows us to distinguish economically meaningful customization from idiosyncratic word choice while measuring temporal evolution in contracting practices. We define the boilerplate in two steps. First, we establish a uniform set of terms by selecting the p most frequently appearing defined terms in a calendar year. This

set, denoted $B_p = [t_1^b, t_2^b, ..., t_p^b]$, determines which concepts are included in the boilerplate, where larger values of p incorporate less common terms. Second, for each term in B_p, we identify the boilerplate definition t_i^b as the definition exhibiting the highest average similarity to all other definitions of the same term in that year.

A.3.3 Extensive measures of contract novelty

We next construct extensive margin measures that capture contract novelty based on which terms are included or excluded, rather than how individual terms are written. These measures complement the intensive margin (textual distance) analysis by quantifying the breadth of definitional coverage.

First, $ExtMgn1$ is the boierplate coverage ratio. This measure captures the proportion of boilerplate terms that appear in contract j:

$$\text{ExtMgn1}_j = \frac{|B_p \cap T_j|}{|B_p|}$$

Higher values indicate more varied adoption of standard boilerplate terminology. A contract including all boilerplate terms receives a score of 1.

Second, $ExtMgn2$ is the contract standardization ratio. This measure captures the proportion of contract j's terms that are drawn from the boilerplate set:

$$\text{ExtMgn2}_j = \frac{|B_p \cap T_j|}{|T_j|}$$

Higher values indicate that the contract's definitional structure relies more heavily on standard terms rather than bespoke definitions.

We also combine the two extensive margin measures into an aggregate novelty index:

$$\text{NOVELTY}_j = 100 \times \left(1 - \frac{1}{2}(\text{ExtMgn1}_j + \text{ExtMgn2}_j)\right)$$

This score ranges from 0 to 100, with higher values indicating greater contract novelty (less boilerplate overlap).

We also calculate other extensive margin measures in the following way. For contracts with available term-level distance calculations, we compute the percentage of terms with definitions sufficiently close

to the boilerplate medroid:

$$\text{PCT.BOILERPLATE}_j = \frac{|t \in T_j : d(t, m_t) < \tau|}{|T_j|} \times 100$$

where $d(t, mt)$ is the angular distance between contract j's definition of term t and the medroid definition, and $\tau = 0.1$ is the distance threshold. This measure captures the intensive margin dimension – how closely definitions match standard language – aggregated to the contract level.

We additionally compute the sum of cosine similarities across all overlapping boilerplate terms:

$$\text{TOTAL SIMILARITY}j = \sum t \in B_p \cap T_j \cos(\theta_{jt})$$

where θ_{jt} is the angle between the embedding vectors of contract j's definition and the medroid definition for term t. Higher values indicate greater aggregate textual similarity to boilerplate language.

A.3.4 Intensive measures of contract novelty

The intensive margin captures variation in how contract provisions are written, conditional on their inclusion. We measure textual distance from standardized language using sentence embeddings and angular distance metrics. We employ the all-mpnet-base-v2 sentence transformer model to convert contract text into dense vector representations. This model maps text sequences to 768-dimensional embeddings optimized for semantic similarity tasks. For each provision type, we compute pairwise cosine similarities and convert these to angular distances:

$$d_{\text{angular}}(u, v) = \frac{\arccos(\text{sim}_{\cos}(u, v))}{\pi}$$

where $\text{sim}_{cos}(u, v)$ denotes the cosine similarity between embedding vectors u and v. Angular distance ranges from 0 (identical) to 1 (orthogonal), providing an interpretable metric of semantic dissimilarity.

For each term or provision type, we identify the medroid – the most representative definition across the corpus. The medroid is the observation with the highest average cosine similarity to all other valid observations:

$$m^* = \arg\max_{i \in V} \frac{1}{|V| - 1} \sum_{j \in V, j \neq i} \text{sim}_{\cos}(e_i, e_j)$$

where V is the set of contracts containing a non-empty definition and e_i is the embedding vector for contract i's definition. The medroid serves as the empirical reference point for measuring deviation from standard language.

For each curated boilerplate term (Gemini or Consensus list), we compute the angular distance from each contract's definition to the term-specific medroid. We then aggregate these term-level distances to the contract level using multiple summary statistics:

1. Mean Angular Distance: Average distance across all boilerplate terms present in the contract
2. Median Angular Distance: Median distance, robust to outlier terms
3. Frequency-Weighted Mean Distance: Weighted average where weights are inversely proportional to term frequency, giving greater weight to less common (potentially more informative) terms:

$$\bar{dj}^{fw} = \frac{\sum t \in B_p \cap T_j w_t \cdot d_{jt}}{\sum_{t \in B_p \cap T_j} w_t}, \quad w_t = \frac{1}{f_t}$$

where ft is the number of contracts containing term t.

Higher distance values indicate greater deviation from standardized boilerplate language, suggesting more customized or innovative definitional choices.

Furthermore, we also calculate EBITDA definition distances specifically given the importance of EBITDA definition carve-outs in credit agreements. We extract EBITDA definitions from each contract and compute angular distances to the corpus medroid. The EBITDA distance measure captures variation in how borrowers and lenders structure the earnings definition, including:

- Add-back provisions (non-cash charges, restructuring costs, transaction expenses)
- Pro forma adjustments for acquisitions and dispositions
- Cap provisions limiting certain add-backs
- Exclusions for extraordinary or non-recurring items

Contracts with higher EBITDA distances employ more customized earnings definitions, potentially reflecting borrower-specific operational characteristics or negotiated flexibility.

Lastly, we extend the intensive margin analysis to negative covenant provisions, computing distances for six covenant categories: liens, indebtedness, investments, restricted payments, asset sales,

and fundamental changes. First, we do the whole-covenant embedding. For each covenant type, we embed the full extracted covenant section text (up to 8,000 characters) and compute angular distances to the type-specific medroid. This captures overall structural and linguistic variation in covenant drafting. We then aggregate covenant-level distances to the contract level. The negative covenant distance measures complement the definitional distance analysis by capturing variation in the operative restrictions themselves, rather than the defined terms used within those restrictions.

Across all intensive margin measures, lower distances indicate greater adherence to standardized language—provisions that closely resemble the typical (medroid) formulation in the corpus. Higher distances indicate textual innovation, whether through novel phrasing, additional provisions, structural modifications, or substantive customization.

A.3.5 Extraction of covenants

Covenants in credit agreements are typically separated into three primary sections: affirmative covenants, negative covenants, and financial covenants. Affirmative covenants often include provisions that require borrowers to provide adequate information to lenders on a periodic basis. Negative covenants restrict borrowers' actions, such as incurring additional debt, paying dividends, or making certain investments. Financial covenants include maintenance conditions that the borrower must meet, such as a maximum debt-to-EBITDA ratio or minimum liquidity levels, to avoid default.

We develop a rule-based natural language processing pipeline to extract covenant provisions from the full text of credit agreements. For negative covenants, we extract six categories of negative covenants commonly found in credit agreements: limitations on liens, indebtedness, investments, restricted payments, asset sales, and fundamental changes (mergers, consolidations, and dissolutions). We first locate the negative covenants section by matching document headers against patterns such as "Article VII – Negative Covenants" or "Section 7.01 Negative Covenants." To avoid false matches in the Table of Contents, we skip entries where adjacent section numbers appear within 50 characters of the match. Section boundaries are determined by identifying subsequent article or section headers, or by detecting transition phrases indicating other covenant categories (e.g., "Events of Default," "Affirmative Covenants"). For each covenant type, we employ a two-stage detection process. First, we search for type-specific terminology (e.g., "liens," "indebtedness," "restricted payments"). Second, we verify the presence of restrictive covenant language within a 200-character window surrounding each term match. Restrictive indicators include phrases such as "shall not," "will not permit," "no Borrower shall," and "except

as permitted." We apply false positive filters to exclude non-covenant uses of terminology (e.g., "lien search," "investment bank," "merger agreement"). Upon detecting a covenant, we extract the full provision text by identifying the section header and determining its boundaries. We detect section endings through multiple signals: subsequent numbered sections, subsection markers for nested provisions, and stop patterns indicating departure from the negative covenants article. Extracted sections must contain covenant indicator language within the first 200-300 characters and meet minimum length requirements (200 characters) to ensure substantive content. We impose a maximum extraction length of 8,000 characters per provision.

For financial covenants, we identify these provisions using a separator-based extraction methodology. Financial covenant provisions typically follow a grammatical structure where the covenant name appears between two types of separators. Before-separators introduce the requirement (e.g., "permit," "maintain," "have"), while after-separators specify the threshold comparison (e.g., "shall not be less than," "greater than," "not to exceed," "at least"). We search for text segments bounded by these separator patterns within a maximum distance of 300 characters. We additionally identify financial covenants through section headers containing known covenant type names. We normalize text spacing to handle OCR artifacts (e.g., "7.15financial" $\rightarrow$ "7.15 financial") and search for patterns matching "Financial Covenants" followed by subsection markers and covenant type names (e.g., "Leverage Ratio," "Interest Coverage Ratio," "Fixed Charge Coverage Ratio"). Extracted covenant names are automatically categorized into standardized types including: leverage ratios, interest coverage ratios, fixed charge coverage ratios, debt service coverage ratios, asset coverage ratios, current ratios, liquidity requirements, net worth requirements, and capital expenditure limitations. Categorization employs keyword matching against the extracted covenant name text.

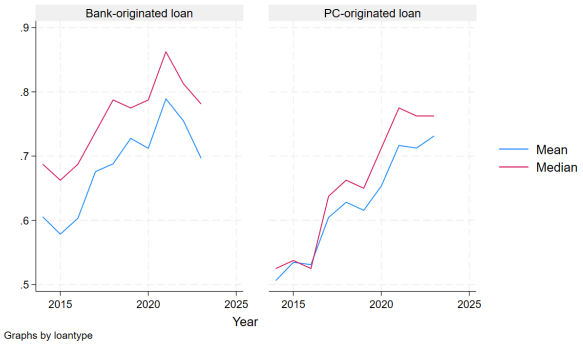
For affirmative covenants, we extract six categories: quarterly financial statements, annual financial statements, annual projections/budgets, monthly financial statements, lender meetings/conference calls, and board observation rights. For each affirmative covenant type, we define required keyword groups that must co-occur within a sentence for a match. For example, quarterly financial statement covenants require simultaneous presence of: (i) temporal indicators ("fiscal quarter," "quarterly"), (ii) document references ("financial statement," "balance sheet"), and (iii) party references ("borrower," "agent," "lender"). A sentence matches only if at least one keyword from each required group is present. We anchor searches at occurrences of "covenants" in the document text and examine subsequent text within a specified offset window (10,000 characters for reporting covenants; 50,000 characters for governance

provisions such as lender meetings and board observation rights). This approach leverages the typical document structure where affirmative covenant provisions follow the covenants section header.

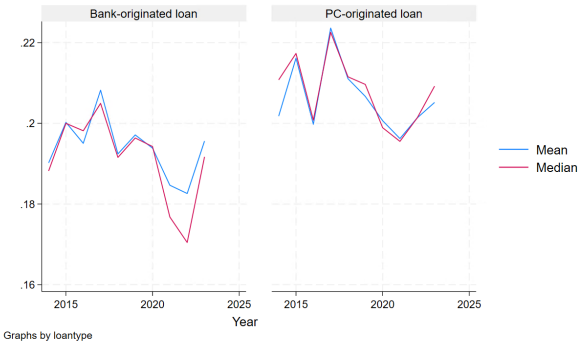
A.3.6 Additional results on contract terms

Figure A4: Extensive measures of customization for bank and non-bank contracts

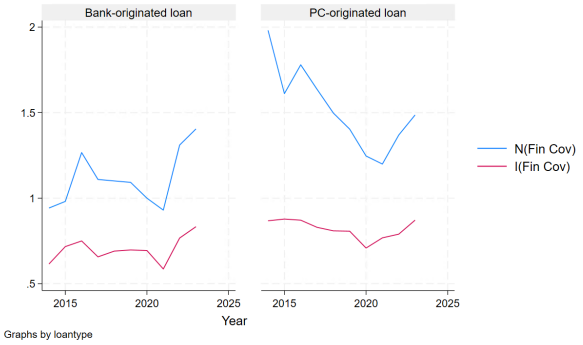
Panel A: Proportion of Boiler Plate Terms in Contract



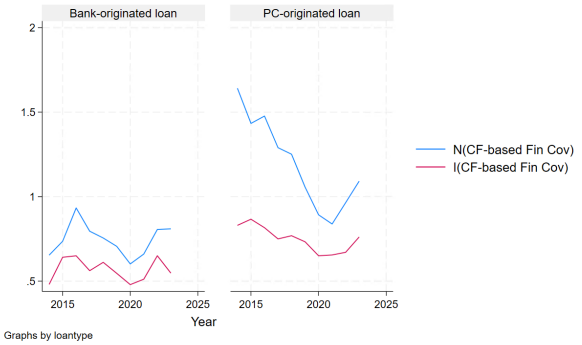
Panel B: Proportion of contract terms in boiler plate



Panel C: Number of financial covenants



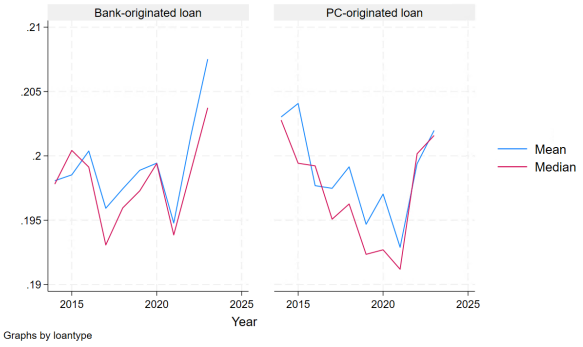
Panel D: Number of cash flow financial covenants



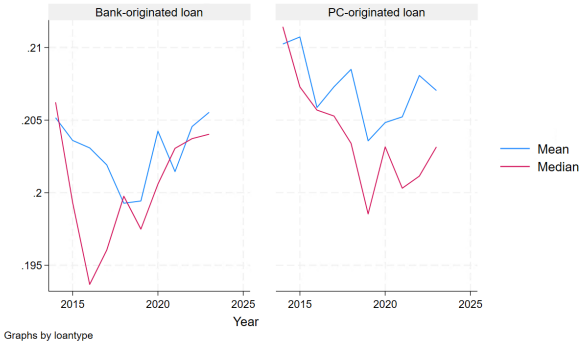
Notes: This figure compares extensive measures of customization between PC-originated and bank-originated loans. Panels A-D show the mean and median for proportion of boiler plate terms in contract (Panel A), proportion of contract terms in boiler plate (Panel B), number of financial covenants (Panel C), and number of cash flow financial covenants (Panel D).

Figure A5: Negative Covenants for bank and non-bank contracts

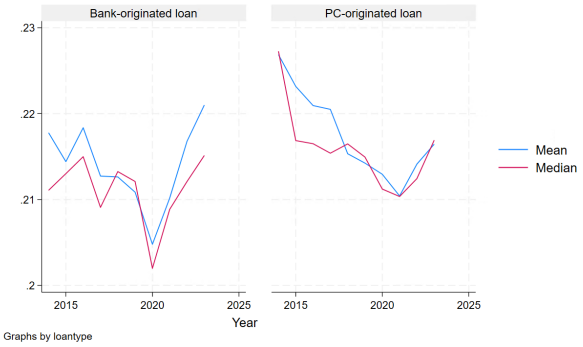
Panel A: Lien



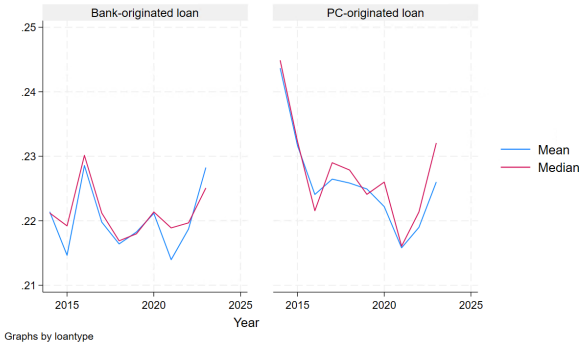
Panel B: Indebtedness



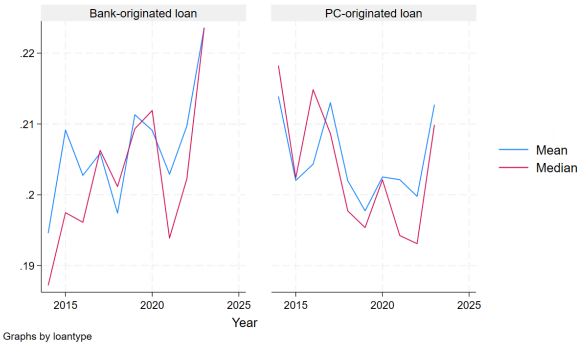
Panel C: Investment



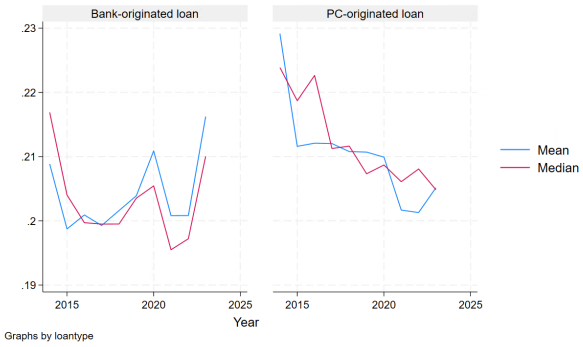
Panel D: Payment



Panel E: Asset sale



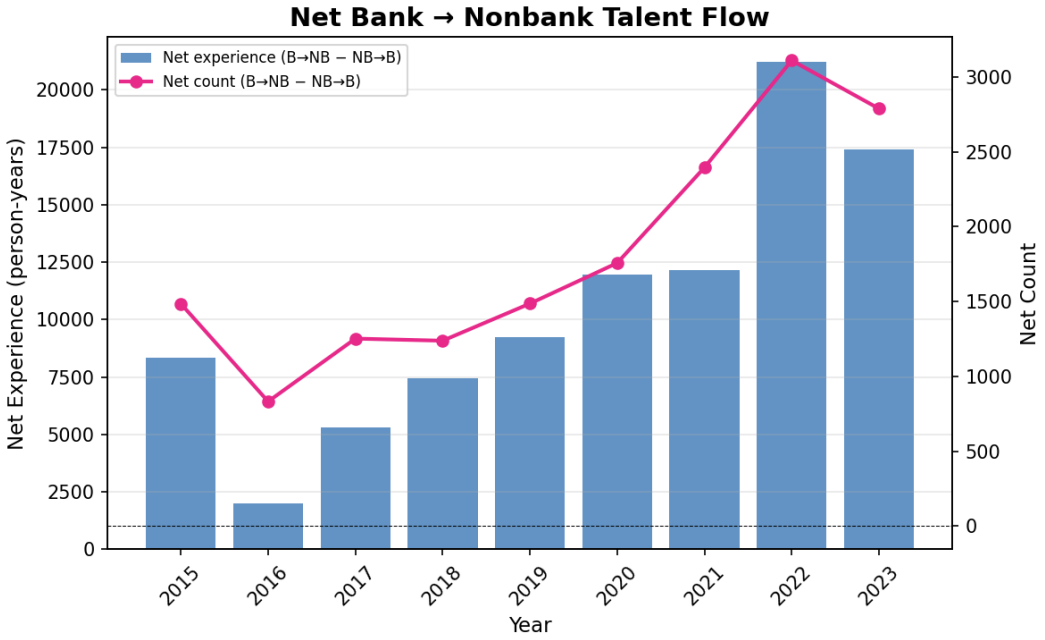
Panel F: Fundamental change



Notes: This figure compares various measures of negative covenants between PC-originated and bank-originated loans. Panels A-F show the mean and median for lien, indebtedness, investment, payment, asset sale, and fundamental change.

B Additional Figures and Tables

Figure B1: Distribution of roles in banks and non-banks



Notes: This figure plots the net flow of talent from banks to nonbanks (bank→nonbank minus nonbank→bank) by year. Bars show net experience in person-years (left axis); the line shows the net headcount of transitioners (right axis). A transition is defined as an individual changing their employer's ultimate parent firm relative to the prior year, where the origin and destination differ in bank/nonbank classification. Positive values indicate a net outflow from banks to nonbanks. Data are from Revelio Labs matched to PitchBook lenders, 2014–2023.

Table B1: Summary Statistics of the Loan Sample: PC-originated vs Bank-originated

	PC-originated						Bank-originated					
	N	Mean	P25	Median	P75	SD	N	Mean	P25	Median	P75	SD
Borrower Characteristics												
Total Assets (USD M)	1,586	357	80	181	386	644	761	1,161	203	428	907	8,284
Ln(Assets)	1,586	25.837	25.107	25.919	26.679	1.299	761	26.757	26.037	26.783	27.533	1.270
Cash/Assets	1,580	0.087	0.019	0.038	0.091	0.134	760	0.069	0.016	0.036	0.073	0.106
Debt/Assets	1,586	0.593	0.361	0.507	0.677	0.590	761	0.660	0.424	0.556	0.741	0.982
Net PP&E/Assets	1,569	0.108	0.015	0.046	0.127	0.165	752	0.117	0.017	0.053	0.139	0.169
EBITDA/Assets	1,586	0.198	0.068	0.117	0.209	0.484	761	0.184	0.064	0.108	0.182	0.582
Junior Loan	1,586	0.106	0.000	0.000	0.000	0.308	761	0.183	0.000	0.000	0.000	0.387
Lender Human Capital												
Sourcing Share	1,586	0.531	0.458	0.542	0.634	0.158	761	0.641	0.599	0.658	0.685	0.070
Diligence Share	1,586	0.661	0.570	0.674	0.740	0.131	761	0.608	0.576	0.602	0.659	0.059
Risk-Approve Share	1,586	0.309	0.228	0.294	0.379	0.116	761	0.459	0.423	0.458	0.478	0.075
Sourcing Experience	1,586	4.225	3.165	3.849	5.267	1.871	761	5.034	4.261	4.958	5.872	1.239
Diligence Experience	1,586	4.970	3.885	4.738	5.687	1.670	761	4.580	3.838	4.508	5.347	1.139
Risk-Approve Experience	1,586	2.305	1.529	2.118	2.801	1.106	761	3.223	2.676	3.146	3.719	0.775
Contract Customization												
No. Definition Terms	1,586	261	193	249	322	106	761	300	228	296	379	128
EBITDA Distance	1,418	0.152	0.118	0.152	0.180	0.040	650	0.137	0.109	0.131	0.160	0.040
Novelty	1,586	57.5	48.7	55.4	63.5	11.8	761	55.0	46.8	50.8	57.1	13.0
Similarity	1,580	47.6	38.3	49.7	60.4	16.0	757	52.0	46.7	57.0	64.3	17.6
Monthly Financials	1,586	0.596	0.000	1.000	1.000	0.491	761	0.306	0.000	0.000	1.000	0.461
Board Observation	1,586	0.211	0.000	0.000	0.000	0.408	761	0.143	0.000	0.000	0.000	0.351
Neg. Cov. Distance	1,394	0.213	0.199	0.212	0.224	0.019	683	0.211	0.197	0.207	0.220	0.021
Lien Distance	1,073	0.197	0.184	0.196	0.206	0.019	531	0.198	0.185	0.196	0.205	0.020
Indebtedness Distance	1,001	0.206	0.191	0.203	0.218	0.023	564	0.202	0.185	0.200	0.213	0.023
Investment Distance	919	0.215	0.203	0.214	0.225	0.021	439	0.213	0.200	0.212	0.223	0.022
Payment Distance	1,132	0.223	0.206	0.225	0.243	0.027	513	0.218	0.199	0.219	0.234	0.027
Asset Sale Distance	470	0.202	0.178	0.197	0.224	0.032	314	0.206	0.183	0.203	0.227	0.032
Fund. Change Distance	823	0.207	0.186	0.210	0.228	0.031	409	0.204	0.185	0.204	0.224	0.029

Notes: Sample covers 2014–2023. The table reports loan-level summary statistics separately for PC-originated and bank-originated credit agreements. Total Assets are in millions of USD. Junior Loan, Monthly Financials, and Board Observation are indicator variables. Lender human capital variables are measured at the firm-year level at the time of loan origination. Distance measures capture how far contract language deviates from standard boilerplate; higher values indicate greater customization.

Table B2: Presence of functions and experience across banks and non-banks - firm level

Panel A: Function Shares

	Sourcing		Diligence		Risk/Approval	
Non-bank	-0.100***	-0.104***	0.045***	0.082***	-0.130***	-0.062***
	(0.012)	(0.025)	(0.011)	(0.022)	(0.011)	(0.021)
Year FE	✓	✓	✓	✓	✓	✓
Controls		✓		✓		✓
Observations	15435	15435	15435	15435	15435	15435
R squared	0.025	0.029	0.006	0.009	0.050	0.064
Mean dep. var.	0.577	0.577	0.627	0.627	0.324	0.324

Panel B: Experience per Classified Employee

	Sourcing		Diligence		Risk/Approval	
Non-bank	-0.809***	-0.382	0.447**	1.381***	-1.189***	-0.413
	(0.170)	(0.334)	(0.175)	(0.374)	(0.122)	(0.266)
Year FE	✓	✓	✓	✓	✓	✓
Controls		✓		✓		✓
Observations	15435	15435	15435	15435	15435	15435
R squared	0.056	0.072	0.043	0.063	0.068	0.076
Mean dep. var.	4.744	4.744	4.847	4.847	2.421	2.421

Standard errors in parentheses, clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1
Notes: This table compares the allocation and depth of lending-function human capital between non-bank firms and banks at the firm-year level. Panel A: The dependent variable is the percentage of employees in each function (sourcing, due diligence, or risk/approval) in a given firm year. We normalize the number of employees in each function by the number of employees available in any function in a given firm year. Panel B: The dependent variable is the total years of functional experience the employees in the firm-year possess divided by the number of classified employees in that firm-year. We consider the ultimate parent firm to define the firm. Controls include PE fund size share, log firm age, and log number of classified employees. Non-bank includes both PE and PC firms.

Table B3: Role of Sourcing and Risk-Approve Human Capital

Panel A: Term Customization

	(1) Novelty	(2) Novelty	(3) Similarity	(4) Similarity
Sourcing Share	-3.323		6.772**	
	(2.303)		(3.071)	
Risk-Approve Share		0.896		-1.977
		(2.325)		(3.201)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Deal type FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	2314	2314	2304	2304
R-squared	0.11	0.11	0.17	0.17

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Covenant Customization

	(1) EBITDA Distance	(2) EBITDA Distance	(3) Neg. Cov. Distance	(4) Neg. Cov. Distance
Sourcing Share	-0.013*		-0.005	
	(0.007)		(0.004)	
Risk-Approve Share		-0.015*		0.003
		(0.008)		(0.004)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Deal type FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	2042	2042	2049	2049
R-squared	0.16	0.16	0.06	0.06

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel C: Monitoring

	(1) Monthly Financials	(2) Monthly Financials	(3) Board Observation	(4) Board Observation
Sourcing Share	-0.206**		-0.042	
	(0.081)		(0.074)	
Risk-Approve Share		0.043		-0.205**
		(0.092)		(0.081)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Deal type FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	2314	2314	2314	2314
R-squared	0.23	0.23	0.04	0.05

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable takes a measure of contractual customization. Panel A reports results for similarity and novelty; Panel B reports EBITDA distance and negative covenant distance; and Panel C reports the requirement of monthly financial statements and board observation rights. The main explanatory variables are an indicator equal to one for a PC-originated loan (and zero if bank-originated), either lender sourcing or risk-approve human capital share, and their interaction. As controls ($\Gamma_{i,t}$), we include a set of time-varying borrower characteristics (size, liquidity, leverage, tangibility, and profitability), as well as an indicator for whether the loan is junior. We include industry, deal type, and year fixed effects, and standard errors are double-clustered at the lender and year levels.

Table B4: Role of Due Diligence Human Capital on the Design of Negative Covenants by Type

Panel A: Lien, Indebtedness, Investment

	(1) Lien	(2) Lien	(3) Lien	(4) Indebtedness	(5) Indebtedness	(6) Indebtedness	(7) Investment	(8) Investment	(9) Investment
PC	-0.000		-0.012	0.004***		-0.016*	0.003*		-0.031**
	(0.001)		(0.009)	(0.001)		(0.009)	(0.002)		(0.014)
Diligence Share		-0.010**	-0.029**		0.028***	-0.002		0.013**	-0.040*
		(0.005)	(0.014)		(0.005)	(0.014)		(0.006)	(0.021)
PC X Diligence Share			0.020			0.031**			0.055**
			(0.015)			(0.015)			(0.022)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1584	1584	1584	1543	1543	1543	1339	1339	1339
R-squared	0.05	0.05	0.05	0.06	0.07	0.08	0.08	0.08	0.09

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Restricted Payment, Asset Sale, Fundamental Change

	(1) Payment	(2) Payment	(3) Payment	(4) Asset Sale	(5) Asset Sale	(6) Asset Sale	(7) Fund. Change	(8) Fund. Change	(9) Fund. Change
PC	0.003*		-0.011	-0.003		-0.000	0.002		-0.013
	(0.002)		(0.016)	(0.002)		(0.023)	(0.002)		(0.019)
Diligence Share		0.019***	-0.003		0.023	0.030		0.006	-0.019
		(0.007)	(0.026)		(0.014)	(0.034)		(0.011)	(0.027)
PC X Diligence Share			0.022			-0.005			0.025
			(0.027)			(0.038)			(0.030)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1622	1622	1622	773	773	773	1216	1216	1216
R-squared	0.08	0.09	0.09	0.10	0.10	0.10	0.08	0.08	0.08

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable takes a measure of negative covenant distance by type. Panel A reports results for lien, indebtedness, and investment, and Panel B reports results for restricted payment, asset sale, and fundamental change. The main explanatory variables are an indicator equal to one for a PC-originated loan (and zero if bank-originated), lender due diligence human capital share, and their interaction. As controls ($\Gamma_{i,t}$), we include a set of time-varying borrower characteristics (size, liquidity, leverage, tangibility, and profitability), as well as an indicator for whether the loan is junior. We include industry, deal type, and year fixed effects, and standard errors are double-clustered at the lender and year levels.

Table B5: Sourcing transitioners: seniority and compensation

Panel A: Indicator

	Seniority		Salary		Total Comp.	
Sourcing Experience at Banks	0.276***	0.299***	4785.301*	5990.084**	9198.517	10461.380
	(0.060)	(0.056)	(2588.931)	(2536.630)	(7232.246)	(7347.213)
Year FE	✓	✓	✓	✓	✓	✓
Controls		✓		✓		✓
Observations	5780	5780	5779	5779	5779	5779
R squared	0.009	0.045	0.028	0.054	0.010	0.026
Mean dep. var.	3.195	3.195	112916.933	112916.933	158737.538	158737.538

Panel B: Years of Experience

	Seniority		Salary		Total Comp.	
Sourcing Experience at Banks (Years)	0.078***	0.078***	3051.101***	3071.482***	5990.061***	5939.295***
	(0.008)	(0.008)	(415.376)	(409.096)	(855.928)	(847.792)
Year FE	✓	✓	✓	✓	✓	✓
Controls		✓		✓		✓
Observations	5780	5780	5779	5779	5779	5779
R squared	0.048	0.081	0.056	0.081	0.035	0.050
Mean dep. var.	3.195	3.195	112916.933	112916.933	158737.538	158737.538

Standard errors in parentheses, clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1
Notes: This table examines whether prior bank sourcing experience predicts seniority and compensation for individuals who transition from banks to nonbanks and work in sourcing roles. Sample consists of bank-to-nonbank transitioners (individuals at a bank in year $t-1$ and at a nonbank in year t), restricted to those who had a job description while at the bank and are currently in a sourcing function at the nonbank. Panel A: the regressor is an indicator for having any prior sourcing experience at a bank; the control group consists of individuals in any other lending function at banks. Panel B: the regressor is years of prior sourcing experience at a bank; the control group is experience in any other lending function. Controls include indicators for MBA, graduate degree, gender, and race/ethnicity. We consider the ultimate parent firm to define the firm.

Table B6: Risk/approval transitioners: seniority and compensation

Panel A: Indicator

	Seniority		Salary		Total Comp.	
Risk/Approve Experience at Banks	0.207**	0.239***	333.785	1735.109	-2485.491	-104.821
	(0.088)	(0.077)	(3553.973)	(3172.489)	(7392.677)	(6674.268)
Year FE	✓	✓	✓	✓	✓	✓
Controls		✓		✓		✓
Observations	4102	4102	4101	4101	4101	4101
R squared	0.007	0.042	0.016	0.040	0.014	0.028
Mean dep. var.	3.062	3.062	109361.907	109361.907	152534.330	152534.330

Panel B: Years of Experience

	Seniority		Salary		Total Comp.	
Risk/Approve Experience at Banks (Years)	0.064***	0.067***	1404.679***	1539.676***	2439.475***	2656.983***
	(0.010)	(0.009)	(391.670)	(366.403)	(926.387)	(835.287)
Year FE	✓	✓	✓	✓	✓	✓
Controls		✓		✓		✓
Observations	4102	4102	4101	4101	4101	4101
R squared	0.029	0.065	0.021	0.047	0.017	0.031
Mean dep. var.	3.062	3.062	109361.907	109361.907	152534.330	152534.330

Standard errors in parentheses, clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1
Notes: This table examines whether prior bank risk/approval experience predicts seniority and compensation for individuals who transition from banks to nonbanks and work in risk/approval roles. Sample consists of bank-to-nonbank transitioners (individuals at a bank in year $t-1$ and at a nonbank in year t), restricted to those who had a job description while at the bank and are currently in a risk/approval function at the nonbank. Panel A: the regressor is an indicator for having any prior risk/approval experience at a bank; the control group consists of individuals in any other lending function at banks. Panel B: the regressor is years of prior risk/approval experience at a bank; the control group is experience in any other lending function. Controls include indicators for MBA, graduate degree, gender, and race/ethnicity. We consider the ultimate parent firm to define the firm.