Reshuffling of Human Capital in Financial Intermediation *

Young Soo Jang† Vrinda Mittal‡ Zirui Song§

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Abstract

How has private credit reshaped human capital in the financial intermediation sector? We document a large migration of personnel from banks to private credit, accompanied by a substantial reshuffling across functions and hierarchies. Exploiting bank stress tests as a shock that induces outflows, we show that movers to private credit attain higher seniority and compensation and experience lower turnover rates. Private credit firms adopt less hierarchical structures with higher senior-to-junior ratios, and allocate more talent towards due diligence roles. Importantly, senior personnel in private credit are more concentrated in due diligence, contrasting with banks where greater focus is placed on deal sourcing and risk control. Private credit loans feature more monitoring and bespoke contractual terms, and these differences are largely explained by the observed organizational and functional differences. Overall, the growth of private credit has implications for not only a reallocation of financial capital but also a reorganization of human capital into structures that enable more information-sensitive lending.

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†Department of Finance, Penn State Smeal College of Business, Email: ykj5180@psu.edu.

‡Department of Finance, Kenan-Flagler Business School, University of North Carolina at Chapel Hill; Email: Vrinda_Mittal@kenan-flagler.unc.edu; Website: https://www.vrindamittal.com/.

§Department of Accounting, MIT Sloan; Email: zrsong@mit.edu.

1 Introduction

Financial intermediation takes many forms and relies on a range of inputs. One form traditionally associated with banks is information-sensitive lending, in which intermediaries undertake costly monitoring of borrowers on behalf of savers (Diamond, 1984).[1] Over the past several decades, such activity by banks within the corporate lending sector has declined secularly, and more recently, a new class of intermediaries—private credit—has emerged to replace this form of lending serving a particular subset of the economy (Buchak, Matvos, Piskorski and Seru, 2024; Jang, Kim, Sufi and Chen, 2026). Despite these developments, relatively little attention has been paid to the workforce composition of the financial intermediation sector. While financial capital can be rapidly reallocated given its fungibility, how this transformation has changed the allocation of human capital within the sector remains an open empirical question.

In this paper, we leverage novel data and develop new measurement approaches to examine how private credit has reshaped human capital in the financial intermediation sector. We study differences in human capital and organizational structures in private credit firms and banks. We evaluate the implications of reshuffling of human capital introduced by private credit for impacted employees' career trajectories and their corresponding value-addition to firms.

Studying these questions presents challenges on both the data and measurement fronts. To address the data challenge, we construct position-level measures of human capital using job description data from Revelio Labs, a repository of public LinkedIn profiles. This allows us to characterize workforce composition across key distinct functions of financial intermediation—such as deal sourcing, due diligence, and risk control—as well as across organizational hierarchies. Furthermore, we assess the real effects of lender workforce composition on corporate lending outcomes. For this, we merge these data with a proprietary database of credit agreements originated by PC firms and banks, and then apply state-of-the-art natural language processing techniques to quantify monitoring intensity and covenant customization.

First, we investigate how the rise of private credit has reshaped workforce composition between banks and private credit (PC) firms. We document a sustained net outflow of workers from banks to private credit firms. Using a panel of personnel switching employers during 2013–2023, we find that

[1] This activity depends heavily on soft information and therefore requires specialized human capital and specific organizational forms, beyond pure financial capital (Stein, 2002; Berger and Udell, 2002; Berger, Miller, Petersen, Rajan and Stein, 2005).

bank-to-PC transitions consistently exceed PC-to-bank transitions throughout the sample period. For example, among personnel switching employers in a given year, the share of bank-to-PC transitions averages over 8%, whereas PC-to-bank transitions remain below 4%. Cumulatively, such persistent net difference leads to more than 2,000 net employee outflows from the banking sector to private credit over the last decade—roughly 17% of the average yearly private credit headcount of around 12,000.

Next, we analyze the career outcomes of employees migrating from banks to private credit (PC) firms. Because matching between banks and PC firms is likely non-random, estimating the causal effect of such moves raises endogeneity concerns. For instance, if PC firms systematically poach the best talent from banks, any positive career effects we observe upon moving to PC would overstate the causal impact. To address this, we construct a Bartik-style instrumental variable that exploits bank stress test shocks, specifically, the interaction between a bank's pre-period share of leavers transitioning to nonbanks (the share component in the shift-share instrument) and its proximity to regulatory capital floors under the stress test compliance threshold (the shift component in the shift-share instrument). This instrument is motivated by Cortés, Demyanyk, Li, Loutskina and Strahan (2020), who document that negative stress test results lead banks to reallocate credit away from riskier loans and towards safer loans. Since riskier loans rely on information-sensitive lending technologies, personnel responsible for these roles would be less needed or may prefer to switch to employers where their value-add would be higher.

Our 2SLS estimates reveal substantially larger effects: seniority, scaled from 1 to 7, increases by 1.4-2.2 after the move.[2] We find similar, quantitatively meaningful effects using alternative measures of seniority, such as the average number of years typically required to attain a given role and an indicator variable equal to one if the position title matches a set of titles commonly associated with senior-level positions. These movers also attain higher additional non-salary compensation, such as bonuses, and experience higher retention rates. Compared to PC-to-bank movers, bank-to-PC movers receive more than $100,000 in additional non-salary pay and are around 4 percentage points less likely to leave by the first year, with the gap widening to around 20 percentage points in year two and three. These results suggest that the reshuffling of human capital from banks to private credit is not merely gap-filling. Rather, it reflects a potentially value-enhancing reallocation, in which workers are better matched in

[2]There are two potential concerns for interpreting the results causally. First, nonbanks naturally try to poach talent away from the banking sector. As a result, leavers to PCs might be on a slightly different career trajectory than other bank employees. Second, employees at stressed banks might have anticipated the stress test results. However, the lack of pre-trends suggest that the subset of complying bank leavers (induced by bank stress test shocks) to banks and PCs follow roughly similar career paths.

terms of value-add at private credit firms than they would have been had they remained in banking.

Next, we investigate how banks and private credit firms differ in how they deploy human capital across different functions and hierarchies. Organizational structures of financial intermediaries can significantly impact how they screen and monitor loans (Berger and Udell, 2002; Stein, 2002; Berger et al., 2005). To examine organizational structures of banks and PC firms, we measure the number of layers of and the shape of corporate hierarchies based on a similar algorithm developed in Ewens and Giroud (2025).[3] The basic idea is as follows: for each bank or private credit firm, we construct internal labor market moves between job titles to arrive at a data-driven "corporate ladder" inside the firm. Then, we select the largest such ladder within the firm and record the number of layers in that ladder. Lastly, we compute the share of individuals in each of the layer of that ladder.[4]

Two main findings emerge. First, PC firms on average have fewer layers (3.78) compared to (4.68). The difference is especially acute when we compare with large (stress-tested) banks, which on average have 8.23 layers. Second, we find that banks exhibit a more hierarchical structure with significantly lower share of employees at the top of the corporate hierarchical pyramid. Coarsening the layers into three-layer or five-layer pyramids, we find that PC firms have around 6-7% more employees in the top layer, and respectively fewer share of employees at the bottom layers. These results suggest the PC firms tend to have a flatter organizational structure.

Based on each employee's job descriptions in LinkedIn, we also classify each employee into one of three core lending functions—sourcing, diligence, and risk control—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). We find that banks allocate a significantly greater share of their workforce to sourcing and risk control, whereas private credit firms are more diligence-intensive. In terms of magnitudes, private credit firms employ 10.5% more workers in diligence roles relative to the sample average, while banks employ 8.9% more in sourcing and 5.4% more in risk control than the sample average.

Why might private credit (PC) firms organize human capital differently across functions and organizational hierarchies? Prior research shows that PC lenders engage in information-sensitive lending that relies heavily on soft information—through close monitoring and relationship-based lending, at least as much as banks for private middle-market borrowers over which they compete (Jang, 2025). We revisit

[3]We also conduct a robustness test using only the seniority measure provided by Revelio Labs. The results are similar.

[4]The detail of the measure construction is documented in Appendix A.4.

this literature through the lens of human and organizational capital. Theory suggests that such lending not only requires specialized human capital, but also a more compact, less hierarchical organizational structure that facilitates the production and transmission of soft information (Berger and Udell, 2002; Stein, 2002; Berger et al., 2005). We observe this pattern empirically in private credit firms. In PC firms, diligence is elevated to a more senior function, consistent with the idea that private credit underwriting relies on experienced judgment in structuring bespoke loans rather than the routine processing of standardized information. In contrast, in banks, greater focus is placed on deal sourcing and risk control while diligence is largely a junior function where standardized credit analyses are performed by analysts and associates.

If PC firms reorganize and redeploy human capital in a way that facilitates lending technologies reliant on soft information, we should expect these human capital differences to translate into greater monitoring or more bespoke lending solutions for borrowers. As the final exercise of this paper, we test this hypothesis by linking workforce composition to loan-level measures of monitoring and contract customization. Applying state-of-the-art natural language processing techniques from prior literature (e.g., Murfin and Sun (2025)) to a proprietary set of credit agreements originated by both PC firms and banks (Jang, 2025), we find that PC-originated loans feature more intense monitoring and customized contractual terms—particularly in highly negotiated covenant provisions—than bank-originated loans. These differences persist even after controlling for borrower characteristics, suggesting that PC firms actively tailor contracts rather than merely replicating standardized agreements.

Crucially, once we control for the lender's organizational structure differences, the PC monitoring and customization premium diminishes or reverses.[5] This suggests that the apparent advantage of private credit lenders in contract customization largely reflects the underlying differences in organization structures. Moreover, once we interact control for the share of diligence employees in the top layer, the differences in contract customization goes away, an interesting effect from the interaction between organizational structure and human capital functions. Hence, the way private credit lenders organize human capital and organizational hierachies and functions appears to have a first-order effect on monitoring intensity and contract customization.

Literature Review. We contribute to multiple strands of literature. First, we contribute to the literature on human capital in financial intermediaries (e.g. Ewens and Rhodes-Kropf (2015), Binfarè, Brown,

[5]This is true either when we use the number of layers or the share of employees in the top layer of the hierarchy as the main explanatory variable.

Harris and Lundblad (2023), Gao, Wang and Wu (2024), Jackson (2025), Schneider, Strahan and Yang (2025)).[6] One of our key contributions is the measurement of human capital in financial intermediation across distinct functions: due diligence, sourcing, and risk control. 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 control roles.[7] 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.

A related, contemporaneous paper in the area that is complementary to ours is Ivashina, Rotermund and Wallace-Wright (2026) that shows the importance of specialized human capital in private credit firms. While that paper similarly documents flows of employees from banks to private credit over recent decades, we depart from it in two principal respects. First, we develop a novel instrumental-variable strategy that yields causal estimates of the seniority, compensation, and retention gains accruing to individuals who move from banks to private credit firms. Second, and more importantly, treating the human capital flows as a motivation, we then examine the organizational and functional differences between private credit firms and banks, and how these differences translate into monitoring intensity and contractual customization.

Second, our findings provide empirical support for linking theories of organizational structure with the practice of information-sensitive lending. The longstanding literature recognizes a variety of information-sensitive functions within both banking and private capital markets, including sourcing, screening, monitoring, relationship lending, and liquidity provision (Diamond, 1984; Berger and Udell, 1995; Diamond and Rajan, 2001; Kashyap, Rajan and Stein, 2002; Degryse and Ongena, 2005; Gompers, Kaplan and Mukharlyamov, 2016; Gompers, Gornall, Kaplan and Strebulaev, 2020). Theories of organizational structure emphasize that information-sensitive lending relying on soft information requires not only specialized human capital but also a more compact and less hierarchical organizational design, which facilitates the production and transmission of such information (Berger and Udell, 2002; Stein, 2002;

[6]More broadly, recent research has discussed multiple forms of intangible capital, amongst which the closest to our research is human capital. See, for example, Bolton, Wang and Yang (2019), Guan, Li, Lu and Wong (2019), Beaumont, Hébert and Lyonnet (2025), Guenzel, Kogan, Niessner and Shue (2025). For further research on other forms of intangible capital, refer to Eisfeldt and Papanikolaou (2014), Crouzet, Eberly, Eisfeldt and Papanikolaou (2022), Eisfeldt, Kim and Papanikolaou (2022), Crouzet and Eberly (2023), Ayyagari, Demirgüç-Kunt and Maksimovic (2024). For customer capital, refer to, Gourio and Rudanko (2014), He, Mostrom and Sufi (2024). This is not an exhaustive list of papers.

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

Berger et al., 2005). We show that PC firms specialize in due diligence human capital, elevate these roles to more senior positions, and organize these functions under a less hierarchical structure than banks. We further demonstrate that these functional differences contribute to the greater monitoring intensity and more bespoke lending solutions that private credit provides compared to banks.

Third, 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, Erel and Prilmeier, 2022; Davydiuk, Marchuk and Rosen, 2024; Haque, Mayer and Stefanescu, 2025; Jang, 2025; Jang, Kim, Sufi and Chen, 2026; 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 (Block, Jang, Kaplan and Schulze, 2024; Jang, 2025; Jang, Kim, Sufi and Chen, 2026), 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 monitor and 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 differences in the lending outcomes.

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 implications of private equity–backed firms (Kaplan and Stromberg, 2009; Davis, Haltiwanger, Handley, Jarmin, Lerner and Miranda, 2014; Mittal, 2022; Isen, Richmond, Smith and Yannelis, 2025). Building on Jang (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 (Murfin and Sun, 2025) to measure the customization of hundreds of loan term definitions, as well as the most heavily negotiated information, financial, and negative covenants.

2 Data and measurement

Our analysis combines three main 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 623 banks and 393 PC firms with 1,449,184 and 22,429 unique individuals respectively from 2013 to 2023.[8] We identify banks and PC firms from a combination of data sources, including commercial datasets for private market activity — Pitchbook, Preqin, and a hand-collected list of publicly listed Business Development Companies (BDCs). We then obtain private credit agreements from a proprietary data provider that allow us to measure contract customization for both private credit and bank loan contracts, comprising 1,612 PC loans and 839 bank loans over the same period. We describe these main data sources and measurement below. Additional details are in Appendix A.1.

2.1 Employer–employee data and function classification

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. 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. To obtain the list of banks and nonbank, we rely on Pitchbook.

Intermediation function classification from job descriptions

Revelio Labs also provides individual-level job descriptions, which we use to classify employees into three broad job functions: sourcing, diligence, and risk control. These functions represent key pillars of credit intermediation (Block et al., 2024; Schneider et al., 2025).[9] Sourcing refers to the process through which intermediaries develop proprietary deal-flow networks that enable them to identify and reach firms seeking financing (i.e., borrowers). Due diligence encompasses borrower-specific activities through which lenders apply their business expertise to assess creditworthiness ("screening"), negoti-

[8] We selected this time frame to align with other datasets we incorporate, including bank stress tests and our proprietary credit agreement sample, which are described in detail later.

[9] Sourcing and due diligence are also central functions of private equity and venture capital investors (Gompers et al., 2016, 2020).

Table 1: Summary Statistics

Panel A: Person-Level

	Banks			Private Credit		
	N	Mean	SD	N	Mean	SD
Has job description	7,595,888	0.44	0.50	138,899	0.50	0.50
Classified into any function	7,595,888	0.31	0.46	138,899	0.27	0.44
Seniority (1-7 scale)	7,595,888	3.29	1.55	138,899	4.05	1.69
Total compensation ($k)	7,595,888	168.23	147.45	138,899	294.37	264.93
Total experience (years)	7,595,888	8.63	8.24	138,899	7.41	6.81
Sourcing experience (years, classified)	7,595,888	6.23	6.55	138,899	5.78	5.76
Classified into sourcing	7,595,888	0.20	0.40	138,899	0.14	0.35
Diligence experience (years, classified)	7,595,888	6.02	6.34	138,899	5.70	5.62
Classified into diligence	7,595,888	0.20	0.40	138,899	0.19	0.40
Risk/Approval experience (years, classified)	7,595,888	5.60	5.89	138,899	5.23	5.18
Classified into risk/approval	7,595,888	0.14	0.35	138,899	0.10	0.29

Panel B: Firm-Level

	Banks			Private Credit		
	N	Mean	SD	N	Mean	SD
Sourcing share	6,216	0.64	0.23	3,994	0.53	0.33
Diligence share	6,216	0.60	0.22	3,994	0.70	0.28
Risk/Approval share	6,216	0.41	0.24	3,994	0.33	0.29
Sourcing experience	6,216	5.14	3.56	3,994	4.09	3.96
Diligence experience	6,216	4.59	3.46	3,994	5.14	4.29
Risk/Approval experience	6,216	3.13	2.73	3,994	2.28	2.92
PE fund size share	6,216	0.00	0.00	3,994	0.36	0.44
Log firm age	6,216	1.58	0.71	3,994	1.58	0.71
Log classified employees	6,216	3.56	2.08	3,994	2.40	1.86

Panel C: Top 10 Private Credit Firms

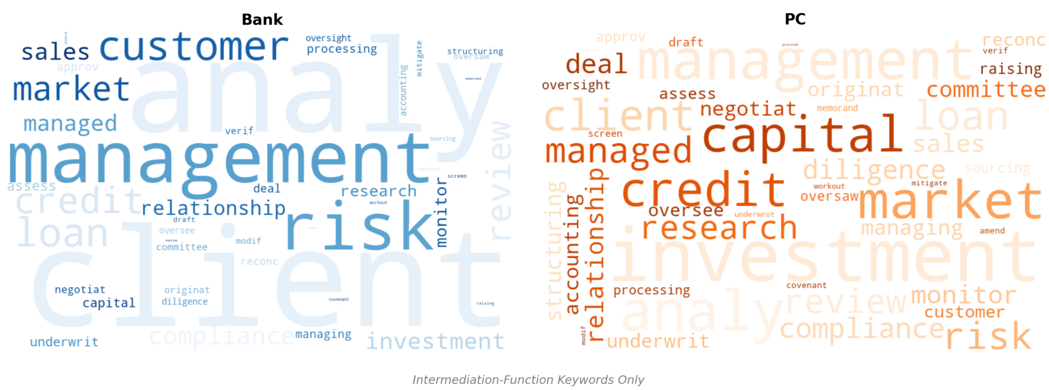
Firm	# of Employees/Year	Employee Share	PC Role (Preqin)	PC Fund Share (PB)
1. Ares Management Corporation	946	8.0%	58.7%	–
2. Barings LLC	741	6.3%	100.0%	85.3%
3. The TCW Group, Inc.	434	3.7%	53.8%	93.0%
4. Apollo Global Management, Inc.	312	2.6%	55.7%	38.9%
5. Angelo Gordon	304	2.6%	82.9%	–
6. Golub Capital Partners LLC	299	2.5%	68.6%	100.0%
7. Blackstone, Inc.	260	2.2%	27.6%	22.1%
8. HPS Investment Partners LLC	221	1.9%	100.0%	98.0%
9. First Eagle Investments	219	1.9%	100.0%	–
10. Kayne Anderson Capital Advisors LP	219	1.9%	–	77.5%

Notes: Sample covers 2013–2023, restricted to banks and private credit firms. Panel A reports person-firm-year level statistics. Sourcing, diligence, and risk/approval are binary indicators for function classification. Diligence combines screening, underwriting, and monitoring. Risk/Approval combines risk assessment and approval functions. Total compensation is in thousands of dollars. Experience variables measure cumulative years of experience in each function. Panel B reports firm-year level statistics, further 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 total years of functional experience divided by the number of classified employees. 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 $\ln(\text{classified employees} + 1)$. Panel C lists the top 10 private credit firms (Revelio rcid level) by average yearly headcount over 2013–2023. MidCap Financial Services is folded into Apollo Global Management (its Pitchbook ultimate parent). *# of Employees/Year* is the mean across years of unique LinkedIn user-positions at the firm in a given year, restricted to positions surviving the 1m PC keep filter; *Employee Share* divides this by the same total summed across all PC firms in the sample. *PC Role (Preqin)* is the parent-level Preqin private-debt activity share (`role_pd`); *PC Fund Share (PB)* is Pitchbook `pc_fundsize / (pc + pe + vc) fundsize` at the rcid level.

ate loan terms ("underwriting"), and oversee performance after origination, such as through the use of covenants ("monitoring"). Risk control captures back-office functions related to risk management and compliance, typically operating under policies and constraints established by a separate credit committee. These roles also reflect the split between front office, middle office and back office. We believe sourcing to be front office, diligence to be middle office, and risk control to be back office. We have job descriptions for 44% (50%) of employees in banks (PCs). We classify employees across their job functions and focused industries based on a carefully-curated list of keywords. Our methodology is described in Appendix A.3.[10]

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 (e.g. customer relationship management), 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-Preqin 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

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

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.[11] Second, we compute function experience intensity: for each firm-year, the total years of prior experience 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 presents the summary statistics of our Revelio sample. Panel A reports the person-year panel summary statistics. The average seniority is higher in private credit relative to banks (4.04 vs. 3.29), indicating that the organizational structure is flatter at PC firms. The standard deviation for seniority is around 1.6 (1.7) for both bank (PC) employees. In line with higher seniority, PC employees on average also receive higher total compensation. With regards to experience, the average bank employee has 8.63 years of experience over 7.41 for PC employees.

Panel B 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 control (0.41 vs. 0.33), while PC firms have a higher diligence share (0.70 vs. 0.60). Turning to experience, PC employees accumulate more diligence experience per classified employee (5.14 years vs. 4.59 for banks), whereas banks have more sourcing experience (5.14 vs. 4.09) and risk/approval experience (3.13 vs. 2.28) 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.

Panel C presents the top 10 private credit firms by their average number of employees in a given year in our sample. We construct our list of PC firms based on Pitchbook and Preqin data. And we also output their share of PC roles (Preqin) and PC fund share (Pitchbook) respectively in the table. When one of both of the shares are above 50%, we take all employees in the given firm as PC employees – such is the case for Ares. When the shares are below 50%, as in the case for Blackstone, we rely on a carefully curated list of credit-related keywords to filter only employees working in credit-related roles based on their raw job titles and descriptions.[12] Since around 50% of employees have missing job descriptions and titles are be generic, our measures for total PC employees are quite conservative.

We also show the top 10 banks (by employee) in Appendix Table B1. As expected, the bulge bracket banks contribute the most number of employees, with Bank of America, Wells Fargo, and JP Morgan be-

[11]We use risk control and risk/approval interachangeably.

[12]The list of credit keywords can be found In Data Appendix Table A4.

ing the top three with around 70,000-80,000 employees annually on credit-related roles, and representing 10%-11% employee share.

2.2 Credit agreement sample

Most of the private credit financing is extended to middle-market firms that are not publicly traded.[13] We rely on a proprietary database from an anonymous third-party appraisal firm commonly used by private credit providers.[14] A key advantage of our data is that we observe the actual credit agreements originated by both banks and private credit firms for privately-held borrowers.

Table 2: 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)	1,612	359	77	181	387	649	839	1,134	218	461	926	7,893
Ln(Assets)	1,612	25.831	25.073	25.920	26.681	1.311	839	26.806	26.110	26.857	27.554	1.230
Cash/Assets	1,606	0.085	0.019	0.038	0.091	0.130	838	0.068	0.016	0.036	0.074	0.104
Debt/Assets	1,612	0.588	0.357	0.505	0.667	0.586	839	0.664	0.424	0.557	0.743	0.960
Net PP&E/Assets	1,594	0.106	0.015	0.046	0.125	0.163	830	0.116	0.017	0.053	0.135	0.168
EBITDA/Assets	1,612	0.202	0.068	0.117	0.209	0.483	839	0.187	0.064	0.108	0.184	0.571
Junior Loan	1,612	0.103	0.000	0.000	0.000	0.304	839	0.197	0.000	0.000	0.000	0.398
Lender Human Capital												
N(Layers)	1,612	4.135	3	4	5	1.508	839	8.226	8	8	9	1.341
T1 Layer Share	1,612	0.434	0.326	0.413	0.581	0.163	839	0.364	0.266	0.317	0.393	0.148
T1 Layer Diligence Share	1,552	0.402	0.226	0.405	0.595	0.239	826	0.336	0.289	0.333	0.427	0.169
Sourcing Share	1,609	0.505	0.433	0.500	0.600	0.162	827	0.551	0.518	0.622	0.638	0.187
Diligence Share	1,609	0.690	0.625	0.714	0.768	0.148	827	0.660	0.602	0.638	0.679	0.125
Risk-Approve Share	1,609	0.311	0.211	0.325	0.400	0.152	827	0.413	0.412	0.459	0.489	0.143
Contract Customization												
No. Definition Terms	1,612	261	193	248	322	105	839	305	233	307	387	127
EBITDA Distance	1,449	0.151	0.118	0.152	0.179	0.040	721	0.137	0.109	0.130	0.159	0.040
Novelty	1,612	57.3	48.7	55.2	63.3	11.7	839	54.8	46.8	50.6	56.9	12.8
Similarity	1,607	47.8	38.6	49.9	60.5	15.9	835	52.4	47.2	57.7	64.4	17.4
Monthly Financials	1,612	0.605	0.000	1.000	1.000	0.489	839	0.279	0.000	0.000	1.000	0.449
Board Observation	1,612	0.220	0.000	0.000	0.000	0.415	839	0.145	0.000	0.000	0.000	0.353
Neg. Cov. Distance	1,424	0.213	0.200	0.212	0.224	0.019	752	0.210	0.197	0.207	0.220	0.021
Lien Distance	1,098	0.197	0.184	0.196	0.206	0.020	588	0.198	0.186	0.197	0.207	0.020
Indebtedness Distance	1,027	0.206	0.191	0.203	0.218	0.024	622	0.203	0.186	0.201	0.214	0.023
Investment Distance	940	0.215	0.203	0.214	0.225	0.021	480	0.213	0.200	0.212	0.223	0.022
Payment Distance	1,158	0.223	0.207	0.225	0.243	0.027	561	0.218	0.199	0.219	0.234	0.027
Asset Sale Distance	488	0.203	0.179	0.198	0.224	0.032	356	0.206	0.183	0.202	0.226	0.032
Fund. Change Distance	844	0.208	0.186	0.210	0.228	0.030	460	0.203	0.184	0.203	0.223	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. N(Layers) is the number of estimated organizational layers at the originating firm; T1 Layer Share is the share of employees in the top layer; T1 Layer Diligence Share is the diligence share within the top layer. 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.

[13] Block et al. (2024) and Jang et al. (2026) report that 75-80% of private credit borrowers are private equity-backed.

[14] 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).

Our final sample contains 2,451 credit agreements (839 "bank-originated" and 1,612 "PC-originated"), extended to private middle market firms between 2014 and 2023. 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 covenants, EBITDA definitions, negative covenant definitions, and (iii) other contractual provisions relevant to monitoring and enforcement of contract terms. We then develop a text embedding algorithm similar to Murfin and Sun (2025) that compares the contractual provisions across these contractual terms. We describe the methodology in greater detail in Appendix A.6.

Table 2 presents summary statistics for financial contracts originated by banks and those originated by nonbanks. 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 $359 mn.

3 From banks to private credit: human capital flows and career outcomes

In this section, we document substantial flows of human capital from banks to nonbanks. We document two main facts: 1) workers pesistently leave from banks to private credit firms, and 2) these transitions are rewarded with higher seniority and associated with higher bonus compensation and retention rates.

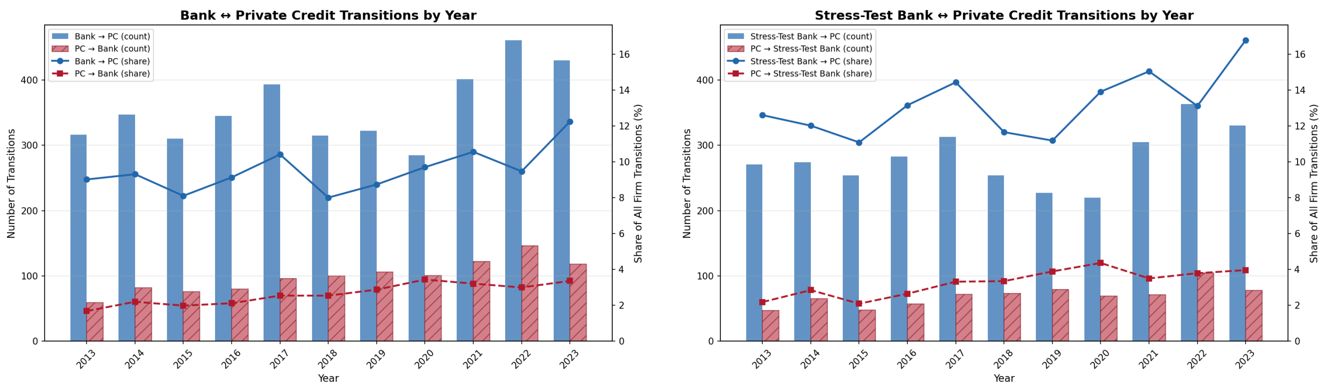
There are two potential concerns for identifying the causal effects of moving from banks to private credit funds for employees' career outcomes. First, the ones that leave their bank is a selective group of individuals. Second, people that leave to work at PCs are likely different from those transitioning to another bank. To isolate the movers that moved to PCs quasi-exogenously, we utilize a novel Bartik-style instrumental variable approach. We document in greater detail the identification strategy in Section 3.2.

3.1 Human capital flows

As a first step, we look at the raw data showing transition of employees between banks and private credit firms. Panel (a) of Figure 2 shows the number of bank-to-PC and PC-to-bank transitions by year from 2013 to 2023. Bank-to-PC transitions consistently exceed PC-to-bank transitions throughout the sample period, indicating a net outflow of human capital from banks to private credit. Among personnel switching employers in a given year, the share of bank-to-PC transitions averages over 8%, whereas PC-to-bank transitions remain below 4%. Panel (b) restricts the bank side to the DFAST stress-test banks used to construct our instrument (Section 3.2). The net outflow is, if anything, more pronounced within this subsample: the bank-to-PC share averages roughly 13% and rises to about 17% by 2023, while PC-to-bank transitions remain near 3%. The talent reallocation we instrument is therefore concentrated among precisely the large, stress-tested institutions at the center of our identification strategy.

Figure B2 in the Appendix documents the net flow in terms of both headcount and experience-years, confirming a persistent net transfer of experienced workers from banks to PC firms.[15]

Figure 2: Transitions between banks and private credit firms



(a) All banks

(b) Stress-test banks (IV sample)

Notes: This figure shows the number of job transitions between banks and private credit (PC) firms in each year from 2013 to 2023. Panel (a) includes all banks; Panel (b) restricts the bank side (both directions) to the DFAST stress-test banks used to construct the Bartik instrument—the same bank universe as the IV sample. Bars show transition counts (left axis); lines show each direction's share of all employer-to-employer moves, including bank-to-bank, PC-to-PC, bank-to-PC, and PC-to-bank transitions (right axis). Data are from Revelio Labs matched to PitchBook-Preqin lenders.

3.2 Effects on seniority

To test whether workers are rewarded for moving to private credit, we compare bank-to-PC movers against bank-to-bank movers using an instrumental variable strategy based on bank stress test shocks and each bank's previous connection with PC firms. Both groups are bank leavers who switch firms, so the design isolates the effect of the destination—moving to a PC firm rather than another bank—conditional on leaving. We construct a panel of 135,348 bank leavers who switch firms during 2013–2022. Of these, 2,727 move to PC firms and 132,621 move to other banks. For each leaver, we observe seniority of their hired position in a ±3-year window around the move. Because our instrumental variable strategy relies on bank stress tests, we further filter to employer transitioners out of stress-tested

[15]While Panel A shows the net flow of human capital from banks to private credit, Panel B documents the same net outflow to private equity/credit firms in general.

banks only. This yields our Bartik sample of 19,218 unique stress-test bank leavers during 2013–2022, of which 1,685 move to PC firms and 17,533 move to other banks. Appendix Table B2 reports the summary statistics of the final sample of unique bank leavers.

3.2.1 Instrument construction

We construct the Bartik-style instruments in the following procedure. First, our shift component comes from bank stress tests. This is motivated by Cortés et al. (2020), who document that negative stress test results lead banks to reallocate credit away from riskier loans and toward safer loans. Because riskier loans rely on information-sensitive lending technologies, personnel responsible for these roles would be less needed or may prefer to switch to employers where their value-add would be higher.

The Dodd-Frank Act Stress Tests (DFAST) are forward-looking exercises mandated by the 2010 Dodd-Frank Act (Section 165(i)(2)) to ensure large financial institutions have enough capital to absorb losses during severe economic downturns. The first stress test takes place in 2012, the start of our main analysis sample period. In particular, these DFAST stress tests provide bank-year level shocks: banks whose projected capital ratios fall closer to regulatory floors under the severely adverse scenario face greater pressure to restructure, creating outflows of human capital.[16]

Following Cortés et al. (2020), we construct the stress test exposure in the following way:

$$\text{stress distance}_{bt} = \min\left(\text{Tier1}_{bt} - 6\%,\ \text{TotalRBC}_{bt} - 8\%,\ \text{Leverage}_{bt} - 4\%\right) \tag{1}$$

where the minimum distance is across three capital ratio floors under the DFAST severely adverse scenario in year t. Banks with smaller (or negative) stress distances are closer to regulatory constraints.

Because stress tests are only binding when the stress test ratios are relatively close to the regulatory thresholds, we have to choose an arbitrary threshold for where our treatment starts. On the other hand, we also want to maintain significant variation so that our first-stage remains highly relevant. As a result, we pick sstress $\text{distance}_{bt} = 1$ as our cutoff for treatment definition. In other words, our first shift is a dummy variable coded as $\mathbf{1}\left[\text{stress distance}_{bt} < 1\text{pp}\right]$. Since stress test results also have different significance based on how close the bank is to the regulatory threshold in a given year, we also construct our second shift instrument that captures the continuous variation of the stress tested ratios as follows: $\max\left(0,\ 1 - \text{stress distance}_{bt}\right)$. This second shift instrument keeps the exposure of stressed bank-years as

[16] We use scenario_id 3, i.e., severely adverse scenario because the test is most salient for that scenario.

well. Appendix Table B3 reports the bank-years in our sample period that are within the stress distance of 1 and therefore our "treated" bank-years.

Our shares are defined as the share of transitions to nonbanks from each bank b in the pre-period. In particular, we calculate the share over 2008-2012. Banks differ in their historical connections to the private credit sector. Some banks have historically served as "pipelines" to PC firms—a larger share of their departing employees transition to PC rather than to other banks. Our share measure intends to capture this dimension.

In the last step, we interact these two components in a Bartik-style instrument. In essence, we construct, for each bank leaver from a DFAST stress-test bank, the following:

$$Z_i^{\text{binary}} = s_b^{\text{NB}} \times \mathbf{1}\left[\text{stress distance}_{bt} < 1\text{pp}\right] \tag{2}$$

$$Z_i^{\text{trunc}} = s_b^{\text{NB}} \times \max\left(0,\ 1 - \text{stress distance}_{bt}\right) \tag{3}$$

where s_b^{NB} is the pre-2013 share of leavers from bank b who went to PC firms (vs. other banks). The binary instrument assigns equal weight to all banks below the 1pp threshold; the truncated version assigns higher weight to more stressed banks.

Our identifying assumption for the Bartik instrument comes from the shift being exogenous (Goldsmith-Pinkham, Sorkin and Swift, 2020). In particular, bank employees cannot predict with certainty whether their bank will fail the stress test because the Fed's supervisory models, assumptions, and adjustments can differ from the bank's internal projections, creating uncertainty in the final outcome. Since our shifters still cover 34 bank-years, the instrument gives us substantial variation to estimate the first-stage.

3.2.2 Baseline 2SLS estimates

We first use the instrumental variable in a static setting, comparing the average employee outcomes three years before and after the transition.

The first stage regression equation is as follows:

$$\text{Post}_{it} \times \text{ToPC}_i = \alpha_i + \gamma_t + \pi \cdot \text{Post}_{it} \times Z_i + \phi \cdot \text{Post}_{it} + \theta \cdot \text{Exp}_{it} + \nu_{it} \tag{4}$$

where π captures the relevance of the Bartik instrument: among stress-test bank leavers in the post-move period, those from banks with higher historical PC pipelines and regulatory stress are more likely to have moved to a PC firm. Importantly, we show that our results are insensitive to using the dummy variable version and the continuous version for the stress test shift variable.

The second stage regression equation is as follows:

$$Y_{it} = \alpha_i + \gamma_t + \beta \cdot \widehat{\text{Post}_{it} \times \text{ToPC}_i} + \delta \cdot \text{Post}_{it} + \theta \cdot \text{Exp}_{it} + \varepsilon_{it} \tag{5}$$

where α_i and γ_t are person and year fixed effects, $\text{Post}_{it} = \mathbf{1}[t \geq 1]$ indicates the post-move period, and $\text{Post}_{it} \times \text{ToPC}_i$ is the endogenous variable instrumented by $\text{Post}_{it} \times Z_i$.

Both stages include person and year fixed effects, so identification comes from within-person variation in stress exposure across cohorts.

Table 3 reports the regression results. Panel B reports the first-stage results. Across all specifications, the F-stat is larger than 20, suggesting strong relevance. Panel A reports the second-stage estimates. The magnitude of the 2SLS estimates reflects the local average treatment effect for compliers—workers whose destination is shifted by stress test exposure. These are plausibly workers recruited into senior PC roles during periods of bank distress, who receive substantial seniority premium upon transitioning. In terms of economic magnitudes, the IV estimate implies that stress-test-induced movers experience a 1.4–2.2 level increase in seniority upon transitioning to private credit.

Two features of the setting help to rationalize the magnitude of this estimate. First, the IV estimate recovers a local average treatment effect (LATE) for compliers—experienced bankers at distressed institutions who would not have left absent the regulatory shock—rather than the average effect across all movers. Second, the large coefficient partly reflects differences in organizational structure: banks maintain deep hierarchies with many management layers, whereas private credit firms are considerably flatter. A mid-level credit officer at a large bank may perform functions equivalent to a senior role at a smaller private credit shop. Taken together, the large LATE is consistent with banking human capital commanding senior roles in the flatter organizations of private credit.

3.2.3 Alternative measures for seniority

Our baseline outcome is the Revelio seniority tier, an ordinal scale running from 1 (most junior) to 7 (most senior). To verify that the estimated seniority premium is not an artifact of this particular coding, we re-estimate the static 2SLS specification using two alternative measures of position seniority. The first, *implied years*, maps each Revelio tier k to the average years of experience held by bank workers

Table 3: Causal effect of moving to private credit: 2SLS

Panel A: Second stage — Dep. var.: Seniority

	Trunc 1.0			Binary 1.0		
	(1)	(2)	(3)	(4)	(5)	(6)
Post × Bank → PC	1.533**	1.536**	2.186***	1.358*	1.377*	2.189***
	(0.673)	(0.673)	(0.752)	(0.798)	(0.793)	(0.810)
KP F-stat	22.0	22.1	22.3	22.8	23.0	22.4
Person FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Exp + Tenure		✓	✓		✓	✓
Bank pre Δsen × Post			✓			✓
Observations	127,269	127,269	127,269	127,269	127,269	127,269
Mean dep. var.	3.483	3.483	3.483	3.483	3.483	3.483

Panel B: First stage — Dep. var.: Post × To PC

	Trunc 1.0			Binary 1.0		
	(1)	(2)	(3)	(4)	(5)	(6)
Bartik × Post	0.717***	0.719***	0.741***	0.334***	0.335***	0.350***
	(0.153)	(0.153)	(0.157)	(0.070)	(0.070)	(0.074)
F-statistic	22.0	22.1	22.3	22.8	23.0	22.4
Person FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Exp + Tenure		✓	✓		✓	✓
Bank pre Δsen × Post			✓			✓
Observations	127,269	127,269	127,269	127,269	127,269	127,269
Mean dep. var.	0.043	0.043	0.043	0.043	0.043	0.043

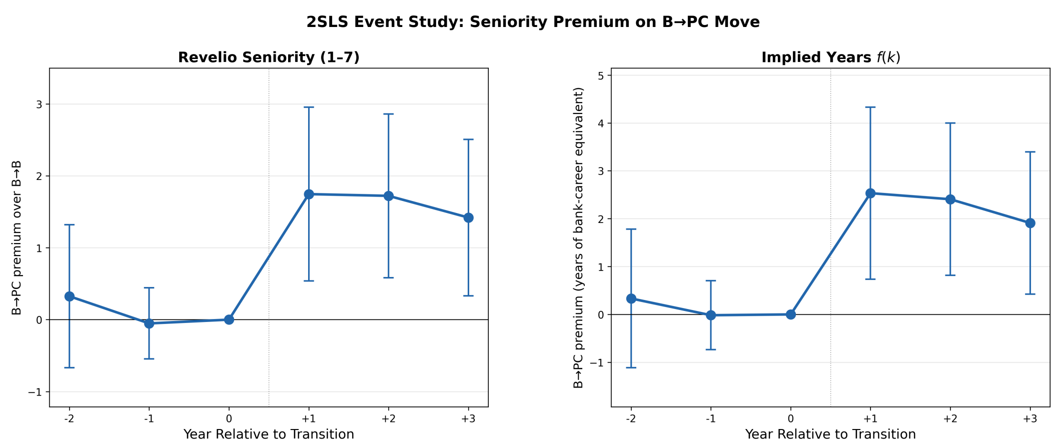
Standard errors in parentheses, clustered at the bank × year level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Notes: Panel 2SLS comparing bank-to-PC movers (treatment) with bank-to-bank movers (control) among stress-test bank leavers. Sample is BB+PC clean panel restricted to event time -2 through $+3$ (omits $t = 0$ as reference). Bank-side keyword filter applied: bank-to-bank controls restricted to leavers whose origin-bank role had a debt/credit/lending keyword or strat_credit classification; bank-to-PC movers retained unconditionally. *Post × Bank → PC* is instrumented with Bartik IV × Post. The Bartik IV interacts the 2008–2012 share of each bank's BB+PC leavers going to PC with the bank's DFAST stress-test distance to regulatory capital floors. Cols (1) and (4): person + year FE only. Cols (2) and (5): + exp_total and tenure-at-current-employer (levels). Cols (3) and (6): + bank pre-period average Δseniority × Post.

at that tier during 2008–2012, computed leave-one-out at the worker $\times$ tier level. This re-expresses the ordinal scale in a cardinal metric, so that the coefficient reads directly in years of equivalent bank career advancement. The second, a *senior-role indicator*, is a binary variable equal to one when the position title contains a senior designation (Managing Director, Partner, Principal, Director, Head of, or a Chief-X-Officer title); it captures discrete promotions into leadership rather than gradual movement along the tier scale.

Table 4 reports the results. Across both instrument variants and all three control specifications, moving to a private credit firm raises seniority under every measure. The implied-years estimates imply that a bank-to-PC move advances a worker by roughly 1.4–3 years of equivalent bank seniority (about 2–3 years under the truncated instrument), and the senior-role indicator shows that the move also raises the probability of holding a senior title. The consistency of sign and economic magnitude across measures indicates that the seniority premium is not driven by how the seniority scale is constructed.

3.2.4 Dynamic 2SLS event study

Figure 3: 2SLS event study (Bartik Trunc 1.0)



Notes: This figure shows the 2SLS event study (Bartik Trunc 1.0) plots for the seniority premium for bank$\rightarrow$PC movers relative to bank$\rightarrow$bank movers. The sample is all bank leavers from 2013 to 2023 working at one of the thirty six stress test banks. The regression includes person and year FE as well cumulative experience control. Each event-time $\times$ ToPC interaction is instrumented with the corresponding event-time $\times$ Bartik IV interaction. The Bartik IV interacts the 2008–2012 share of each bank's leavers going to PC firms with the bank's DFAST stress test distance to regulatory capital floors. $t = 0$ is the last year at the origin bank (reference); $t = +1$ is the first year at the destination firm. Standard errors are clustered at the bank $\times$ year level. The Blue bars represent 95% confidence intervals.

To examine the dynamic effects of exogenous moves from banks to PCs, we generalize the static

Table 4: Alternative seniority measures: Bartik 2SLS

Panel A: Implied years of equivalent bank career advancement

	Trunc 1.0			Binary 1.0		
	(1)	(2)	(3)	(4)	(5)	(6)
Implied years $f(k)$	2.167***	2.171***	3.066***	1.353	1.382	2.516**
	(0.788)	(0.785)	(0.801)	(1.299)	(1.286)	(1.202)
KP F-stat	23.4	23.4	23.9	23.6	23.9	23.2
Observations	123,621	123,621	123,621	123,621	123,621	123,621
Mean dep. var.	7.11	7.11	7.11	7.11	7.11	7.11

Panel B: Senior-role indicator (0/1)

	Trunc 1.0			Binary 1.0		
	(1)	(2)	(3)	(4)	(5)	(6)
Senior-role indicator	0.654	0.659	0.673*	0.612**	0.623**	0.639**
	(0.409)	(0.408)	(0.405)	(0.299)	(0.295)	(0.290)
KP F-stat	17.5	17.5	17.6	21.3	21.7	21.4
Observations	111,788	111,788	111,788	111,788	111,788	111,788
Mean dep. var.	0.16	0.16	0.16	0.16	0.16	0.16

Standard errors in parentheses, clustered at the bank × year level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
Notes: Each panel reports a separate Bartik 2SLS regression on the same panel (event time $\in [-2, +3]$, event year $\leq$ 2022, ST origin banks; person + year FE, bank-year cluster). The endogenous variable is *Post* × *Bank* → *PC* (or PE/PC for the PE/PC sample), instrumented by Bartik IV × Post. Cols (1) and (4): person + year FE only. Cols (2) and (5): + exp_total and tenure-at-current-employer (levels). Cols (3) and (6): + bank pre-period average Δseniority × Post. In Panel A, the dependent variable converts each Revelio seniority tier k to the mean years of experience at that tier among bank workers in 2008–2012 (leave-one-out at the (user, k) level), so the coefficient reads directly in years of equivalent bank career advancement. In Panel B, the dependent variable is an indicator equal to one if the title contains MD/Partner/Principal/Director/Head of/Chief X officer.

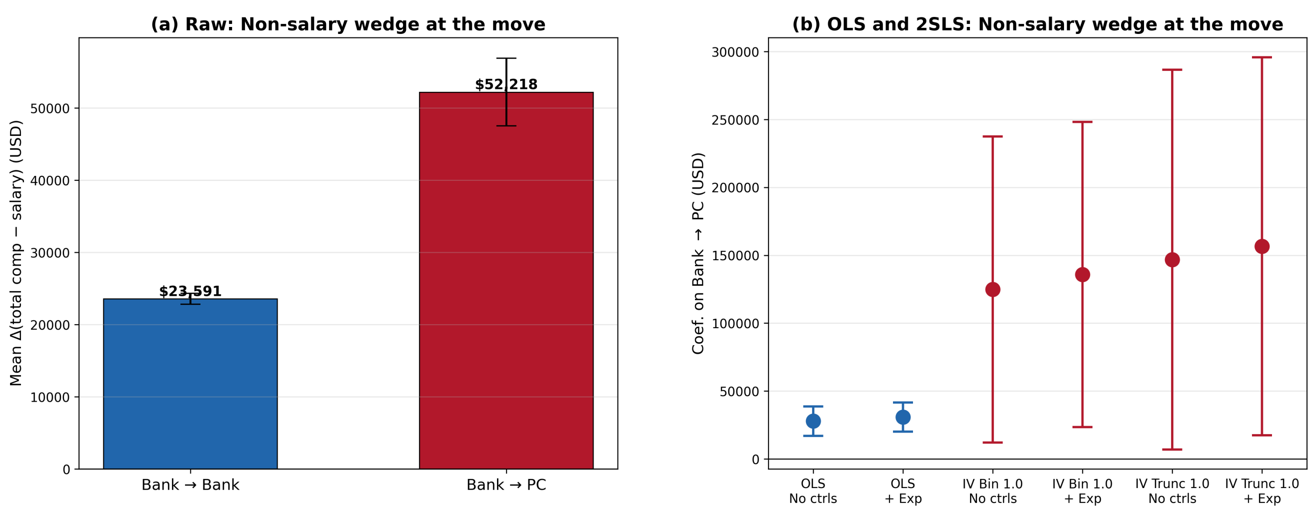
specification in the previous section to a dynamic event study specification as follows:

$$Y_{it} = \alpha_i + \gamma_t + \sum_{k \neq 0} \beta_k \cdot \widehat{\mathbf{1}[k] \times \text{ToPC}_i} + \sum_{k \neq 0} \delta_k \cdot \mathbf{1}[k] + \theta \cdot \text{Exp}_{it} + \varepsilon_{it} \tag{6}$$

where $\mathbf{1}[k] \equiv \mathbf{1}[\text{event time} = k]$, $t = 0$ is the last year at the origin bank (reference period), and each $\mathbf{1}[k] \times \text{ToPC}_i$ is instrumented with the corresponding $\mathbf{1}[k] \times Z_i$. The β_k coefficients trace out the causal seniority premium at each horizon. Figure 3 reports the results. Pre-trends are flat: neither $t = -2$ nor $t = -1$ is statistically distinguishable from zero and the point estimates sit near zero, suggesting that our instrumented bank-to-PC transition is approximately exogenous. Right after the transition, movers to PCs experience an increase in seniority of about 1.7 levels, and the premium remains in the 1.4–1.7 range at $t = +2$ and $t = +3$, indicating a persistent gain in seniority following the move to PC.

3.3 Effects on compensation

Figure 4: Non-salary compensation wedge at the move: bank→PC vs. bank→bank



Notes: Panel (a) plots raw means of $\Delta\text{NonSalary}_i = [\text{TotalComp}_i^{\text{post}} - \text{Salary}_i^{\text{post}}] - [\text{TotalComp}_i^{\text{pre}} - \text{Salary}_i^{\text{pre}}]$ separately for bank→bank and bank→PC movers, with 90% confidence intervals. Panel (b) plots OLS and 2SLS coefficients on the bank→PC indicator from a long-difference regression of $\Delta\text{NonSalary}_i$ at the per-leaver level. "No ctrls" includes event-year FE only; "+ Exp" adds cumulative experience at the move. The two IV variants instrument the bank→PC indicator with each origin bank's pre-period (2008–2012) share of leavers to PC interacted with the DFAST stress-test distance to capital floors (Binary 1.0 = indicator for distance below 1 pp; Truncated 1.0 = $\max(0, 1 - \text{dist})$). Error bars are 90% confidence intervals from origin-bank × event-year clustered standard errors. Sample: stress-test bank leavers, 2013–2022. The full regression table is in Appendix Table B4.

Beyond seniority, we examine whether the move to private credit is also rewarded in dollar terms. Revelio reports two compensation series at the position level: *base salary* and *total compensation*, both imputed from a combination of self-reported pay, peer benchmarks, and external data sources. The difference, total compensation − salary, captures the variable component of pay—bonus, carried interest, equity, and other performance-linked items—that is widely viewed as the dominant margin on which PC firms compensate investment professionals relative to commercial and investment banks.[17] For each bank leaver we compute the change in this non-salary wedge at the move,

$$\Delta\text{NonSalary}_i \;=\; \left[\text{Total Compensation}_i^{\text{post}} - \text{Salary}_i^{\text{post}}\right] \;-\; \left[\text{Total Compensation}_i^{\text{pre}} - \text{Salary}_i^{\text{pre}}\right],$$

where the pre-period is the end of the leaver's last position at the origin bank and the post-period is the start of the first position at the destination firm. By taking a within-mover difference, this measure nets out any cross-sectional level differences in how Revelio imputes compensation across firms and isolates the change in variable pay associated with the transition.

Panel (a) of Figure 4 reports raw means of $\Delta\text{NonSalary}_i$ separately for bank-to-bank and bank-to-PC movers. Bank-to-PC movers gain markedly more variable pay at the move than bank-to-bank movers, with non-overlapping 90% confidence intervals.

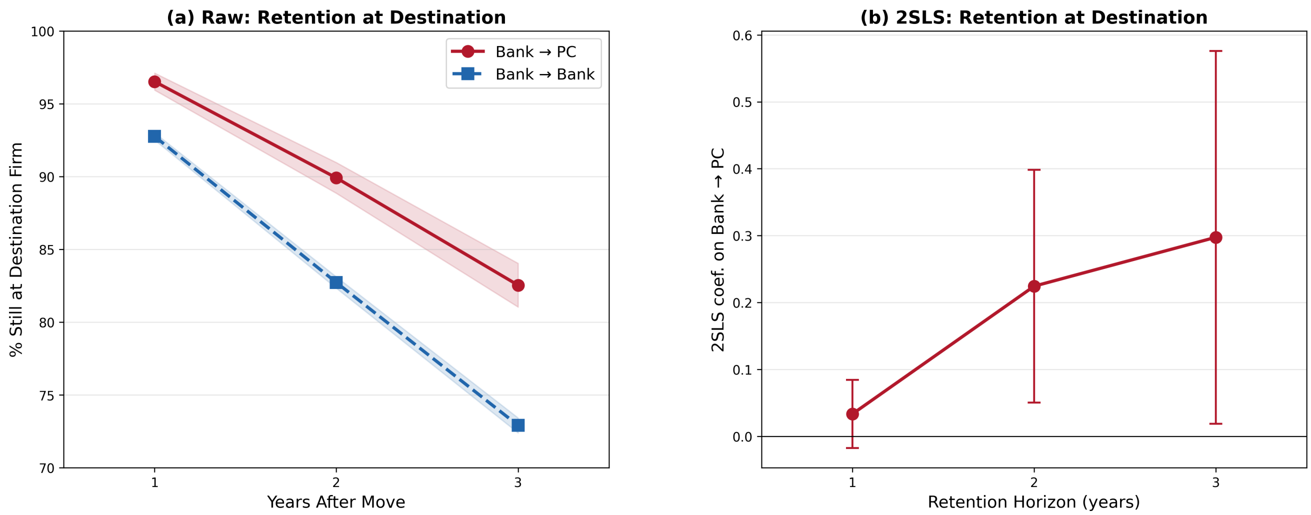
The full set of OLS and 2SLS regression estimates is reported in Appendix Table B4. Panel (b) of Figure 4 visualizes the same six estimates: the first two markers are OLS (with and without controls for cumulative experience at the move), and the remaining four are 2SLS coefficients instrumenting the bank-to-PC indicator with the Binary 1.0 and Truncated 1.0 Bartik instruments. The OLS estimates imply a non-salary wedge of roughly \$28,000–\$31,000 per year for bank-to-PC relative to bank-to-bank movers, statistically significant at the 1% level. The 2SLS estimates are substantially larger—between \$125,000 and \$157,000 per year—suggesting that compliers (workers whose destination is shifted by bank stress-test exposure) earn an even larger non-salary premium upon moving to PC than the average mover. Taken together, the seniority results in Section 3.2 and the non-salary-wedge results here indicate that the bank-to-PC move is rewarded both in rank and in variable pay.

3.4 Effects on retention

We next examine whether the seniority gains from moving to PC are durable by studying retention at the destination firm. If PC firms offer better career prospects, we would expect bank-to-PC movers to remain at their destination longer than bank-to-bank movers.

[17] Kedia, Tai and Wang (2026) show that Revelio compensation measures capture both within-firm and cross-firm differences well, with relative magnitudes closely matching those documented by Song, Price, Guvenen, Bloom and von Wachter (2019) using U.S. Social Security data.

Figure 5: Retention at destination firm: bank→PC vs. bank→bank movers



Notes: Panel (a) plots raw retention rates (fraction still at destination firm) for bank→PC and bank→bank movers with 90% confidence intervals. Panel (b) plots 2SLS coefficients from instrumenting the bank→PC indicator with the Bartik IV (Truncated 1.0: pre-period PC share $\times$ $\max(0, 1 - \text{dist}_{bt})$) with 90% confidence intervals. The dependent variable is $\mathbf{1}[\text{tenure at destination} \geq k]$ for $k = 1, 2, 3$ years. Cumulative experience control and year fixed effects included. Standard errors clustered at the bank $\times$ year level. Sample restricted to stress-test bank leavers, event years 2013–2022.

Panel (a) of Figure 5 plots raw retention rates. Bank-to-PC movers are consistently more likely to remain at their destination: 96.5% vs. 92.8% after one year, with the gap widening to 82.5% vs. 72.9% after three years. Panel (b) presents causal estimates using our Bartik IV strategy. We instrument the bank-to-PC indicator with the interaction of each origin bank's pre-period (2008–2012) share of leavers going to PC firms and the DFAST stress test shock as above. The 2SLS estimates show that moving to PC increases the probability of remaining at the destination firm by 3.3 percentage points at one year, rising to 29.8 percentage points at three years. This evidence suggests that bank leavers going to PC firms experience better matches for their human capital expertise and therefore stay longer at their destination firms.

Together, these results establish that the rise of private credit involves a significant reshuffling of human capital in financial intermediation. Workers flow from banks to PC firms at increasing rates, and these transitions are rewarded with higher seniority and compensation as well as lower turnover rates ex post.

4 Functional and Organizational Differences in Banks and Private Credit

While the preceding section documents human capital flows between banks and private credit lenders, it remains an open question whether these flows translate into firm-level differences in human capital composition and organizational structure. In this section, we shift focus from individual workers to examine, more holistically, how banks and private credit firms differ in organizing and deploying their human capital across various intermediation functions.

4.1 Organizational differences

To show organizational differences between banks and private credit firms, we start by constructing a notion of hierarchy. We want to capture how steep or flat the organization structure is, i.e., the number of layers, and the percentage of individuals in each layer, i.e., the shape of the organization structure. Our main measure follows a four-stage construction following Ewens and Giroud (2025). First, we map raw job titles to a canocical role taxonomy. Second, for each bank and PC firm we identify the largest internal labor market based on transitions of employees within the firm. Third, we obtain the rank for each role and the number of layers within each firm. Fourth, pooling all distinct workers observed in firm f between 2013 and 2023, we count workers per firm, aggregate to the layer level, and compress each firm's K_f layers onto a common axis of three coarse layers (bottom/middle/top) or five quintile buckets using a bottom-heavy consecutive-layer partition (e.g., $K = 8$ splits as 3/3/2 for three layers and 2/2/2/1/1 for five quintiles), summing worker shares within bucket and normalising so the bucket shares sum to one per firm.. The detailed constructions is described in Appendix A.4. We show the overall three-layer and five-quintile pyramids in Figure 6 here and the function-level decomposition in Figure 8. We also construct organizational structures based on Revelio's seniority measure and are in Appendix Figure B1. The results remain robust.

Table 5 shows the differences in the number of layers between banks and PC firms using the internal labor market moves from 2013 to 2023 following Ewens and Giroud (2025). These number of layers are not mapped to quintile and tercile buckets to show variation in the raw number of layers across firms. We find that banks on average have approximately one more layer (4.68) relative to PC firms (3.78). Within banks, there is a stark difference in the average number of layers between the stress-test banks (8.23) and the other banks (4.38). This is consistent with our intuition, as the stress test banks have more employees and a vertical structure can help to organize information and work flow. Smaller banks will have fewer employees and hence a flatter hierarchial structure may suffice. Overall, we find that PC firms typically have flatter corporate hierarchies than banks, with fewer layers between the deal professional and the investment committee.

Table 5: Number of hierarchical layers per firm

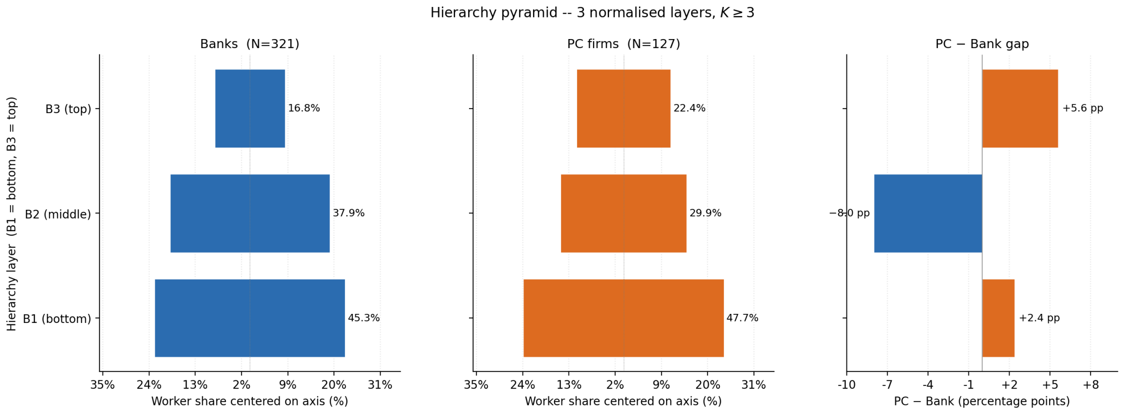
Sample	N	Mean	Median	Std	Min	p25	p75	Max
Banks	374	4.68	4.0	1.93	2	3.0	6.0	10
Stress-test banks	30	8.23	8.0	1.07	5	8.0	9.0	10
Other banks	344	4.38	4.0	1.66	2	3.0	5.0	10
PC firms	173	3.78	4.0	1.42	2	3.0	5.0	7

Notes: Firm-level summary statistics on the number of hierarchical layers (K). K is the SpringRank + GMM/AIC layer count, post-processed with a mass-weighted floor that merges any singleton-role layer whose worker share falls below 10% of the firm's largest-ILM person-years. Sample restricted to bank and PC firms with at least one observed internal-labor-market transition ($K \geq 2$), using the firm definition of Table 1, over 2013–2023. *Stress-test banks* are the subset of banks undergoing stress tests between 2013 and 2022; *Other banks* are the other banks in the sample.

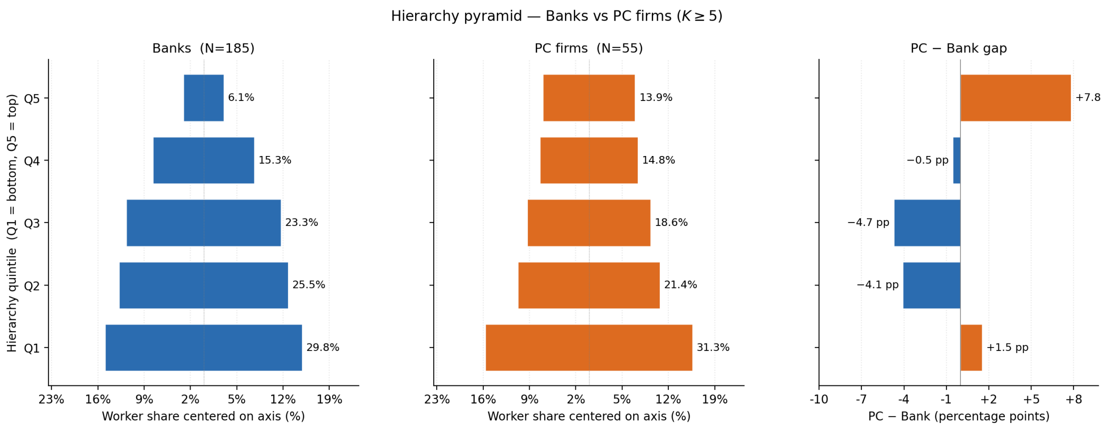
Figure 6 shows the shape of the bank and PC firm organization structure. Panel A shows the hierarchy pyramids for banks and PC firms with three layers. The top layer of banks have less number of employees (16.8%) while the top layer of PC firms have 22.4% employees. The bottom layer of banks have 45.3% of employees while PC firms have 47.7% employees. On the other hand, the middle layer of PC firms is thinner (29.9% employees) relative to the middle layer of banks (37.9% employees). Panel B shows the similar hierarchy pyramids, but with five layers instead. We find similar results. PC firms tend to have more employees at the top, while banks tend to have more employees in the middle layers. We find similar results using the seniority measure from Revelio. Figure B1a illustrates this difference using Revelio's seniority classifications: banks exhibit a steep pyramidal structure with 77.1% of employees at the junior and mid tier (seniority levels 1–4), compared to 75.2% at PC firms. Conversely, PC firms have 24.8% of employees at the senior tier (levels 5–7), compared to only 22.9% at banks.[18]

[18] Revelio classifies employees along a seven-point seniority scale, with 1 denoting the most junior and 7 the most senior position within a firm. To better reflect the three-tier pyramidal structure typical of banks and private credit firms, we aggregate these scores into three groups: junior (levels 1–2), mid-level (3–4), and senior (5–7).

Figure 6: Hierarchy pyramids: Banks vs. private credit firms (overall)



(a) Three-layer pyramid ($K \geq 3$)



(b) Five-quintile pyramid ($K \geq 5$)

Notes: Firm-weighted average worker share by hierarchy layer, using the SpringRank + GMM/AIC layer measure. Panel (a) compresses each firm's K layers into three normalised buckets (bottom / middle / top) and is restricted to firms with $K \geq 3$, retaining the mid-size PC firms that fall below the $K \geq 5$ threshold of Panel (b). Panel (b) bins the within-firm relative position k/K into five quintiles and is restricted to firms with $K \geq 5$. In each panel the right sub-figure reports the per-bucket PC−Bank gap in percentage points (positive $\Rightarrow$ PC firm heavier at that bucket). Sample years: 2013–2023.

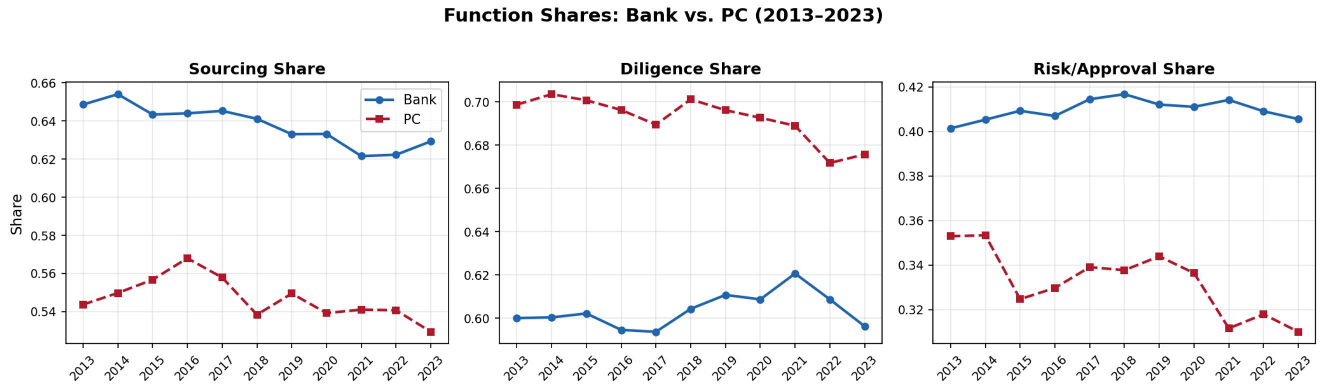
4.2 Human capital functional differences

First, we examine how banks and PCs differ in their specialization in the three core intermediation functions: sourcing, diligence, and risk/approval. In particular, we examine the distribution of those three functions in banks and PCs over time, as a percentage of employees whose job descriptions can be classified in at least one of the functions.

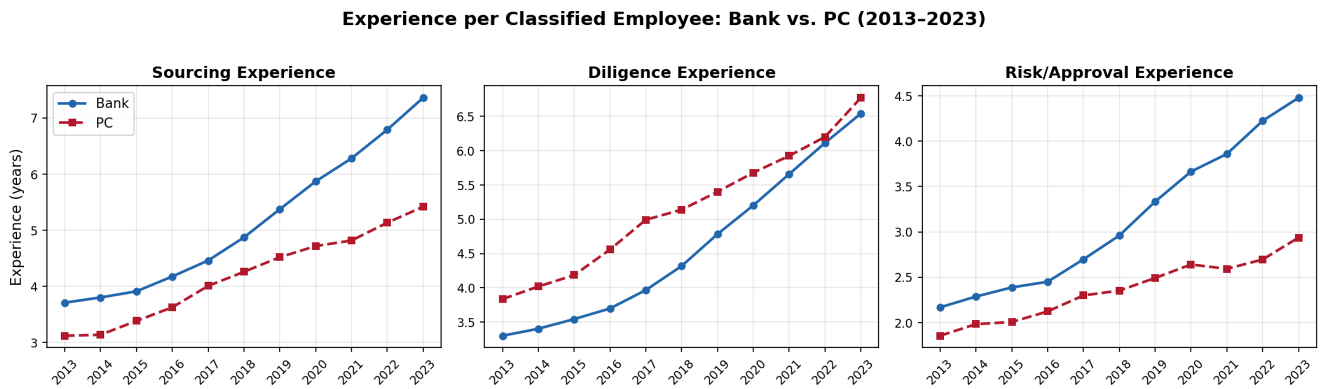
Figure 7 shows the results. Panel A shows that PCs have a larger share of diligence roles compared to banks, while banks have a larger share of sourcing and risk/approval roles. These differences are stable over the sample period, suggesting persistent organizational differences in how the two lender types allocate human capital across intermediation functions. Panel B complements these patterns by

Figure 7: Function Shares and Experience: Bank vs. Private Credit (2013–2023)

Panel A: Function Shares



Panel B: Experience per Classified Employee



Notes: This figure shows how banks and PC firms differ in their specialization in three core intermediation functions. The sample is from 2013 to 2023 and restricted to PC and bank firm-years with at least one function-classified employee. Panel A plots the yearly mean function share. Panel B plots the yearly mean experience per classified employee. Solid blue lines represent banks; dashed red lines represent private credit firms.

plotting the average function-specific experience per classified employee over time. Banks accumulate more sourcing and risk/approval experience per classified employee than nonbanks, while PCs build a comparative advantage in diligence experience—mirroring the compositional differences documented in Panel A.

Table 6 examines these differences more formally, regressing functional role shares (Panel A) and functional experience (Panel B) on a nonbank (PC) indicator for the 2013–2023 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 63.8%. A coefficient of 11.9% implies that private credit firms have 18.7% more diligence roles compared to the average in the sample. On the other hand, we observe that banks have 17.4% more sourcing roles than the average 60.2% classified sourcing roles, and 18.4% more risk approval roles than the average 37.5% in the sample.[19]

Panel B shows the presence of total years of functional experience per classified employee at the firm 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 4.7 years. Private credit firms have 0.4 years more diligence experience per employee, which is 8.5% 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 B5 includes both private equity and private credit firms in the nonbank sample and finds similar results. This is reasonable as most of the private credit deals have private equity sponsors. These results highlight the importance of diligence roles and experience in private credit firms relative to banks.

4.3 Connecting functional and organizational differences

In this section, we further look at the organizational structures by functional roles. Figure 8 shows that banks' pyramidal structure differentiated from PC firms' straight structure is consistent across the three broad functions (diligence, sourcing, and risk control).[20]

This organizational difference has direct implications for the value of human capital in financial intermediation. In banks, junior workers likely produce standardized inputs that are reviewed and synthesized by senior officers. In PC firms, the loan officers across all three functions tend to have higher seniority, and therefore exercises more discretion. As a result, the PC firms not only demand more experienced diligence employees but also amplifies the returns to their expertise (Stein, 2002).

[19] These function-share results are robust to restricting the sample to firm-years with greater classification coverage. In Table B6 we re-estimate Panel A on firm-years where at least 25% of employees are classified into a lending function, or with more than 5 or 10 classified employees; the nonbank (PC) coefficients on all three function shares retain their sign and statistical significance across every cut.

[20] Appendix Figure B1b reports the analogous by-function decomposition using Revelio's seven-point seniority scale as a robustness check, and shows the same qualitative pattern: PC firms employ substantially more mid-level and senior staff, while banks concentrate workers at the junior tier, in every function.

Table 6: Presence of functions and experience across banks and non-banks - firm level

Panel A: Function Shares

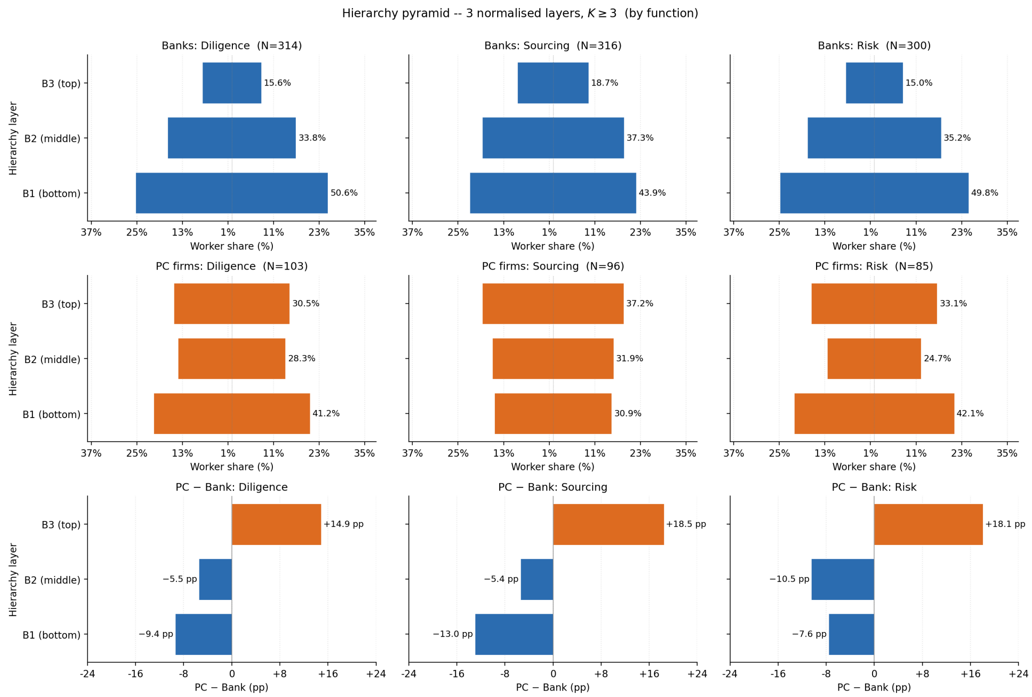
	Sourcing		Diligence		Risk/Approval	
Non-bank (PC)	-0.099***	-0.089***	0.110***	0.105***	-0.075***	-0.054***
	(0.017)	(0.019)	(0.015)	(0.016)	(0.016)	(0.017)
Year FE	✓	✓	✓	✓	✓	✓
Controls		✓		✓		✓
Observations	9934	9934	9934	9934	9934	9934
R squared	0.028	0.031	0.039	0.042	0.017	0.031
Mean dep. var.	0.604	0.604	0.637	0.637	0.381	0.381

Panel B: Experience per Classified Employee

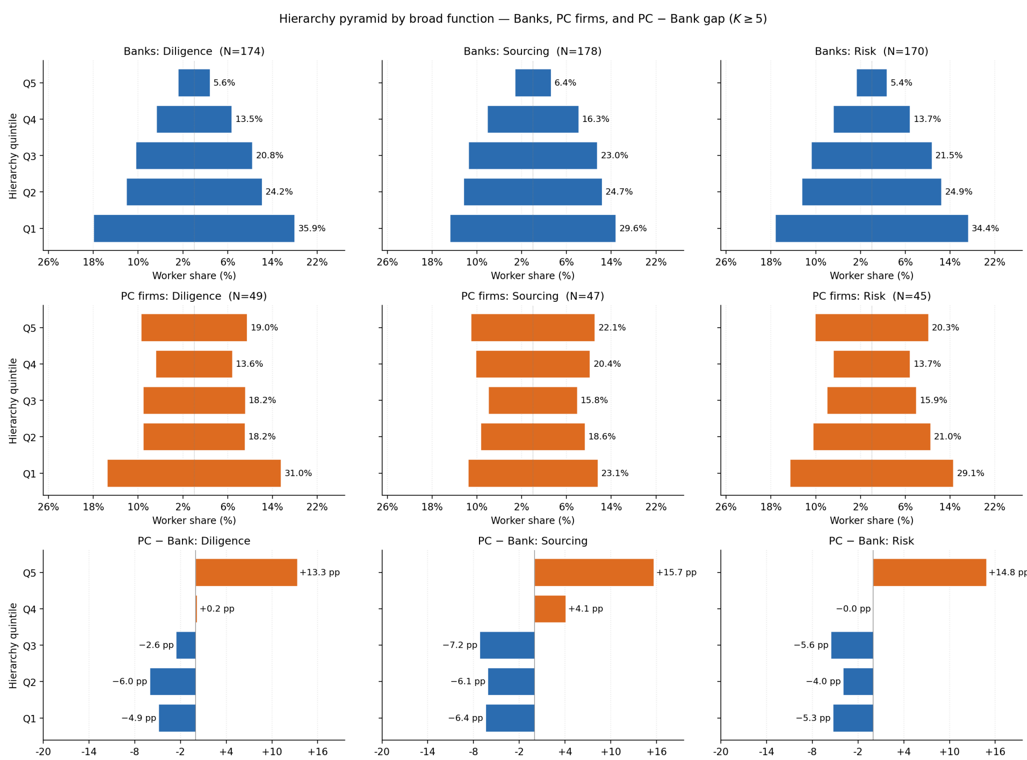
	Sourcing		Diligence		Risk/Approval	
Non-bank (PC)	-0.935***	-0.797***	0.439*	0.335	-0.861***	-0.713***
	(0.231)	(0.246)	(0.229)	(0.258)	(0.174)	(0.192)
Year FE	✓	✓	✓	✓	✓	✓
Controls		✓		✓		✓
Observations	9934	9934	9934	9934	9934	9934
R squared	0.088	0.099	0.075	0.081	0.061	0.067
Mean dep. var.	4.792	4.792	4.808	4.808	2.848	2.848

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 8: Hierarchy pyramids by function: Banks vs. private credit firms



(a) Three-layer pyramid, by function ($K \geq 3$)



(b) Five-quintile pyramid, by function ($K \geq 5$)

Notes: Firm-weighted average worker share by hierarchy layer, using the SpringRank + GMM/AIC layer measure, split by broad function (diligence, sourcing, risk). Panel (a) compresses each firm's K layers into three normalised buckets and is restricted to firms with $K \geq 3$. Panel (b) bins the within-firm relative position k/K into five quintiles and is restricted to firms with $K \geq 5$. In each panel the bottom row reports the per-bucket PC−Bank gap in percentage points (positive $\Rightarrow$ PC firm heavier at that bucket). Sample years: 2013–2023. The overall (all-worker) pyramid is in Figure 6.

Berger and Udell (2002) show that small banks with flat hierarchies are better able to collect and act on soft information about borrowers. A parallel logic applies here: PC firms' organizational structure may allow personnel with diligence expertise to communicate and act on soft information more effectively than in banks. The returns to diligence human capital are therefore likely higher in PC firms not only because the workers are more skilled, but because the organizational form better leverages their skills.

These results establish that banks and PC firms deploy human capital in fundamentally different ways: PC firms are diligence-intensive, while banks emphasize sourcing and risk management. Furthermore, PC firms tend to have higher senior to junior worker ratios and that difference in organization hierarchy is the most acute in diligence functions. We square this finding with our human capital flow results in Section 3.1. Transition flows are concentrated among diligence workers, who experience the largest seniority gains upon moving to PC. This suggests that diligence human capital is particularly important—and particularly valued—in private credit lending.

5 Real implications for corporate lending

What are the real implications of the observed reshuffling of human capital between banks and private credit? In this section, we show that private credit firms' greater emphasis on due diligence human capital is linked to more intensive monitoring and increased contract customization at the subsequent loan level.

5.1 Monitoring and contract customization differences across lenders

We first present a set of robust empirical evidence showing that PC loan include more contractual customizations relative to bank loans. To do so, we construct contract customization measures at the contract level for bank and nonbank 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 9 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

Figure 9: Similarity measures for bank and nonbank 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.

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 9 Panel C shows the average similarity scores for credit agreements by banks and nonbanks 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 nonbank 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.[21] 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

[21]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).

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 B7), 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. This also aligns with the survey evidence in Block et al. (2024) showing that 85% of U.S. private credit funds interact with their portfolio companies at least once per month, compared with 50% for syndicated loan lenders documented in Gustafson, Ivanov and Meisenzahl (2021).

Taken together, these results suggest that, private credit lenders include more bespoke terms and engage in more intense monitoring. They are also more actively involved in customizing the definitions of EBITDA, a key input for most financial covenants, as well as negative covenants that restrict borrower activities. However, these differences are unconditional and do not account for differences in borrower characteristics. Moreover, it remains unclear whether organizational and human capital differences can explain the observed patterns. We investigate these questions in Section 5.2.

5.2 Role of organizational structure

In this section, we examine the empirical relationships between the measures of monitoring and contract customization, lender type (i.e. private credit versus bank), and the lenders' underlying organizational structure differences.

Our main specification follows the following functional form:

$$y_{i,j,t} = \alpha + \beta_1 \mathbb{I}_{PC_j} + \beta_2 H_{j,t} + \beta_3 (\mathbb{I}_{PC_j} \times H_{j,t}) + \beta_4 \Gamma_{i,t} + FEs + \epsilon_{i,j,t} \tag{7}$$

where $H_{j,t}$ denotes a measure of organizational structure 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 loan contract measures from Section 5.1 —

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 monitoring intensity or 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 organizational structure measures associated with monitoring intensity or contractual customization? This relationship is reflected in β_2 when $H_{j,t}$ is the main explanatory variable. Third, does a organizational structure matter more for one type of lender than the other? This will be captured by β_3 on the interaction term. Finally, if organizational structure is indeed an important determinant of those lending outcomes, can the observed organizational differences between private credit lenders and banks explain the observed differences in contractual customization? We assess this by examining how the estimate of β_1 changes in specifications that also include the other variables.

Table 7 reports the estimation results using the number of layers as the primary measure of human capital. 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). The estimated coefficients are statistically significant at the 1% level or higher. 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 16%, 19%, 18%, and 10% of their respective standard deviations. For the monitoring terms, the differences are relatively larger, at 18% and 7%, compared with mean frequencies of 49% 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. The differences in monitoring intensity are particularly meaningful economically. Private credit loans are associated with an 18-percentage-point higher likelihood of requiring monthly financial reporting and a 7-percentage-point higher likelihood of granting board observation rights, both substantial relative to the baseline means of 61% and 22%, respectively.

Turning to Columns (2) and (5) across panels, we find that lender's number of hierarchical layers is negatively associated with five contract customization measures (Novelty, Similarity, EBITDA distance, and the requirement of monthly financial statements and board observation rights) at the 1% significance level. These results are consistent with the view that a lender with flatter organization hierarchical structure facilitates the design of more customized contracts and the inclusion of stronger monitoring rights.

Finally, Columns (3) and (6) across panels show that, once we control for the number of layers, 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 monitoring and loan customization stems largely from their flatter organization hierarchy (Stein (2002)). In fact, without these differences, the results imply that private credit lenders might customize less.

Table 8 shows the same results as above, but for the share of employees in banks and PCs in the top tercile ranking of the organizational hierarchy. Similarly, we find that the share of people in the top tercile explains the observed contractual and monitoring differences between bank and PC loans, further highlighting the importance of organizational structure.

5.3 How human capital interacts with organizational structure

The preceding analyses established two facts in parallel. Section 5.1 showed that PC-originated loans are more customized and involve more intense monitoring than bank-originated loans on every dimension we measure (Novelty, Similarity, EBITDA Distance, negative-covenant distance, monthly financial reporting, and board observation rights). Section 5.2 then showed that this PC–bank gap is largely absorbed once we control for the lender's organizational structure: a flatter hierarchy, and a larger share of employees in the top tercile of the within-firm rank distribution, account for most of the PC effect on monitoring and customization. What remains open is whether the relevant organizational margin is hierarchy *per se*, or hierarchy interacted with the functional mix of human capital at the top of the firm. Section 4.2 documented that PC firms not only have flatter hierarchies but also place a much larger share of diligence personnel near the top. We now combine these two threads to ask whether the observed advantage of PCs is best understood as an organizational effect, a human-capital effect, or the

Table 7: Role of Number of Layers

Panel A: Term Customization

	Novelty			Similarity		
	(1)	(2)	(3)	(4)	(5)	(6)
PC	1.951***		-3.428	-3.095***		5.572
	(0.644)		(3.043)	(0.882)		(4.297)
N(Layers)		-0.462***	-0.784**		0.737***	1.266**
		(0.130)	(0.350)		(0.176)	(0.490)
PC X N(Layers)			0.556			-0.894
			(0.406)			(0.573)
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	2417	2417	2417	2408	2408	2408
R-squared	0.12	0.12	0.12	0.17	0.17	0.17

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***		0.003	0.002**		-0.006
	(0.002)		(0.008)	(0.001)		(0.005)
N(Layers)		-0.001***	-0.001		-0.000	-0.000
		(0.000)	(0.001)		(0.000)	(0.001)
PC X N(Layers)			0.000			0.001**
			(0.001)			(0.001)
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	2143	2143	2143	2147	2147	2147
R-squared	0.16	0.16	0.16	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	0.179***		-0.181	0.073***		0.139*
	(0.027)		(0.111)	(0.017)		(0.072)
N(Layers)		-0.031***	-0.042***		-0.013***	0.004
		(0.006)	(0.013)		(0.004)	(0.008)
PC X N(Layers)			0.047***			-0.012
			(0.015)			(0.011)
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	2417	2417	2417	2417	2417	2417
R-squared	0.28	0.28	0.29	0.05	0.05	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 clustered at the lender by year level.

Table 8: Role of Top Tercile Human Capital Share

Panel A: Term Customization

	Novelty			Similarity		
	(1)	(2)	(3)	(4)	(5)	(6)
PC	1.951***		0.275	-3.095***		-1.598
	(0.644)		(1.663)	(0.882)		(2.329)
T1 Layer Share		3.425*	-0.122		-4.681*	-1.072
		(1.864)	(3.407)		(2.528)	(5.198)
PC X T1 Layer Share			3.949			-3.372
			(4.115)			(6.045)
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	2417	2417	2417	2408	2408	2408
R-squared	0.12	0.11	0.12	0.17	0.17	0.17

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***		0.009*	0.002**		0.003
	(0.002)		(0.005)	(0.001)		(0.003)
T1 Layer Share		0.014***	0.017*		-0.001	-0.001
		(0.005)	(0.009)		(0.003)	(0.006)
PC X T1 Layer Share			-0.008			-0.001
			(0.011)			(0.007)
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	2143	2143	2143	2147	2147	2147
R-squared	0.16	0.16	0.16	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	0.179***		0.361***	0.073***		0.085*
	(0.027)		(0.066)	(0.017)		(0.046)
T1 Layer Share		0.140*	0.400***		0.105*	0.105*
		(0.073)	(0.146)		(0.059)	(0.061)
PC X T1 Layer Share			-0.479***			-0.042
			(0.171)			(0.099)
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	2417	2417	2417	2417	2417	2417
R-squared	0.28	0.26	0.29	0.05	0.05	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 clustered at the lender by year level.

joint product of the two.

Table 9 re-runs the regressions of Section 5.2, replacing the top-tercile aggregate share with the *T1 Layer Diligence Share*—the share of employees in the firm's top hierarchy layer who are classified as diligence personnel. This measure embeds both margins simultaneously: it varies with the firm's hierarchy (which workers reach the top layer) and with its functional mix (how many of those top-layer workers do diligence). Columns (1) and (4) re-display the unconditional PC effects from Table 8; columns (2) and (5) report the partial effect of the T1 Diligence Share alone; columns (3) and (6) include PC, the T1 Diligence Share, and their interaction jointly.

Panel A shows that, for term-level customization, the T1 Diligence Share alone is positively associated with Novelty and negatively associated with Similarity, in the same direction as the PC effect. When the two are entered jointly, the PC main effect attenuates by more than half and loses statistical significance, while neither the standalone T1 share nor the PC×T1 Diligence interaction is significant. The natural reading is that the PC–bank gap in term customization runs through having a top hierarchy layer populated by diligence personnel, rather than through being a PC firm *per se*.

Panel B presents a slightly different pattern for the EBITDA-definition distance. The PC×T1 Diligence Share interaction is positive and significant, even though the main effect of the T1 Diligence Share alone is small and statistically indistinguishable from zero in the joint specification. In other words, having a diligence-heavy top layer raises EBITDA customization *more at PC firms than at banks*, consistent with diligence personnel and the PC organizational form acting as complements when bespoke covenant definitions need to be written. The negative-covenant-distance results in columns (4)–(6) move in the same direction but are noisier and not significant.

Panel C shows the cleanest contrast with the customization results. For both monitoring outcomes—the requirement of monthly financial reporting and the right to board observation—the T1 Diligence Share is not significant either alone or interacted with PC, and the PC main effect remains essentially unchanged when these terms are added (0.184 vs. 0.179 for monthly financials; 0.062 vs. 0.073 for board observation). Monitoring intensity therefore appears to be a PC-specific contractual choice that is *not* mediated by the diligence-share margin: PC firms write more monitoring rights regardless of the functional composition of their top hierarchy layer.

Taken together, these results separate two organizational mechanisms behind PC's contracting advantage. Term-level customization (the way contract language is drafted) and bespoke EBITDA definitions reflect the joint product of organizational form and the concentration of diligence human capital

Table 9: Role of Top Tercile Diligence Human Capital Share

Panel A: Term Customization

	Novelty			Similarity		
	(1)	(2)	(3)	(4)	(5)	(6)
PC	1.951***		0.929	-3.095***		-1.000
	(0.644)		(1.366)	(0.882)		(1.962)
T1 Layer Diligence Share		3.158**	0.696		-4.407**	0.456
		(1.489)	(3.055)		(1.969)	(4.468)
PC X T1 Layer Diligence Share			2.554			-5.267
			(3.491)			(4.950)
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	2417	2346	2346	2408	2337	2337
R-squared	0.12	0.11	0.12	0.17	0.17	0.17

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***		-0.002	0.002**		0.001
	(0.002)		(0.004)	(0.001)		(0.002)
T1 Layer Diligence Share		0.017***	-0.002		0.003	0.001
		(0.004)	(0.008)		(0.002)	(0.005)
PC X T1 Layer Diligence Share			0.021**			0.003
			(0.009)			(0.006)
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	2143	2075	2075	2147	2078	2078
R-squared	0.16	0.17	0.17	0.07	0.07	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	0.179***		0.184***	0.073***		0.062*
	(0.027)		(0.062)	(0.017)		(0.037)
T1 Layer Diligence Share		0.062	0.053		0.056	0.026
		(0.053)	(0.135)		(0.044)	(0.066)
PC X T1 Layer Diligence Share			-0.041			0.017
			(0.148)			(0.087)
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	2417	2346	2346	2417	2346	2346
R-squared	0.28	0.25	0.27	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 clustered at the lender by year level.

at the top of the firm—consistent with diligence workers needing the discretion afforded by a flat hierarchy to design tailored contractual language. Monitoring rights, by contrast, are not explained by the human-capital margin and instead appear to be a contractual choice that PC lenders make independently of their workforce mix.

6 Conclusion

In this paper, we examine how the rise of private credit has reshuffled and reorganized human capital in financial intermediation. We document a sustained migration of personnel from banks to private credit firms, where movers experience higher seniority and non-salary compensation, as well as lower turnover, indicating a better alignment between worker skills and employer needs. Private credit firms, in contrast to banks, adopt less hierarchical structures with a greater concentration of senior personnel in due diligence functions, reflecting a deliberate organizational design to support information-sensitive lending. These differences in workforce composition are not merely structural: they directly translate into more customized covenants, higher monitoring intensity, and bespoke contract terms, highlighting how human capital allocation underpins private credit's distinctive approach to financial intermediation relative to banks.

More broadly, our study provides empirical support for linking theories of organizational structure with the practice of information-sensitive lending. By measuring human capital across distinct functions—sourcing, diligence, and risk control—and across hierarchical tiers, we show that private credit firms specialize labor to enhance the production and transmission of soft information, whereas banks concentrate more on sourcing and risk control. We also provide the first evidence that banks tend to have more hierarchical structures while private credit firms tend to be flatter. These insights underscore the importance of considering workforce composition alongside financial capital in understanding the evolution of credit markets.

Looking ahead, these shifts in human capital composition raise important questions for both research and policy. Do they represent a persistent reallocation of credit across borrower types, and what are the broader welfare implications? Do different forms of organizational structure help achieve financial intermediaries an efficient form of credit origination? Moreover, because specialized human capital is not fully portable (Gao et al., 2024), these changes are unlikely to be easily reversible. Recent regulatory developments—such as the December 2025 rollback of the Leveraged Lending Guidance[22]—seek to enable banks to reenter riskier, information-sensitive lending. Whether such measures can meaningfully reverse the market share gains that private credit firms have secured in these segments remains an open empirical question.

[22]See https://www.mayerbrown.com/en/insights/publications/2025/12/leveraged-lending-guidance-withdrawn-by-occ-and-fdi

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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 2,451 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.

A.1.3 Defining the intermediaries from Pitchbook, Preqin, and BDCs

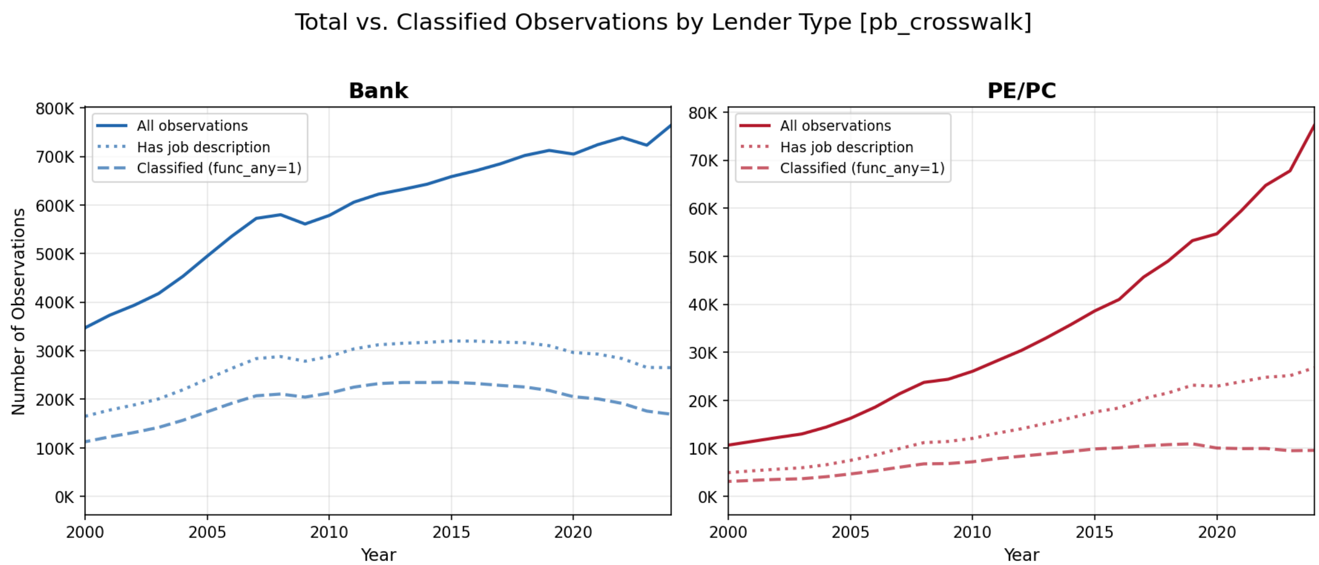
A key challenge in studying officer human capital in private credit is defining a consistent set of intermediaries. We construct the universe of private-credit firms as the union of three sources: (i) Pitchbook firms tagged as private-credit lenders, (ii) Preqin private-debt manager records, and (iii) a hand-collected list of publicly-listed Business Development Companies (BDCs). The Pitchbook universe captures the core set of dedicated PC shops; Preqin extends coverage to private-debt arms of multi-strategy alternative asset managers; the BDC list adds publicly listed credit vehicles that do not always appear with a PC tag in Pitchbook. Together these three sources scope our analysis to the set of institutions that are active in private lending during our sample period.

A.1.4 Linking Revelio, Contracts, and Pitchbook

To merge human capital information to contract-level customization measures, we construct crosswalks between Revelio Labs, Pitchbook, Preqin, and hand-collected BDC list 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, (5) cleaned company name with headquarters location, and (6) phone numbers.

A.1.5 Final sample and unit of observation

Figure A1: 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.

Our baseline unit of observation is the *contract–intermediary* 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.

A.2 Identifying credit-relevant roles in banks and PC firms

We apply two layers of keyword-based filters to identify "credit-related" workers symmetrically on the bank side and the PC side.

- **Layer 1** is the upstream position-level scope filter applied to every Revelio bank or PC position before any downstream step. It drops positions whose title is clearly non-lending / non-investment / non-FT (Table A1); every firm-level, person-level, and hierarchy analysis in the paper inherits it. On the PC side the analogous scope filter is the curated PC firm list (PitchBook PC + Preqin private-debt managers + BDCs).

- **Layer 2** defines the subsample of credit-relevant bank workers used for the bank-to-PC movers analysis (career-mobility / Bartik IV pipelines in Section 3.2) and for two appendix figures that target credit-active bank workers (transition trends and top titles by layer). Bank positions enter this subsample if they are credit-relevant by job-description classifier, substring keyword (Table A2), or qualified title pattern (Table A3); all firm-level analyses (HC regressions, hierarchy build, pyramid, Lincoln deliverable) use only Layer 1.

Layer 1 (position-level scope filter)

Bank-side: a position is dropped if `title_raw` matches any exclusion category in Table A1. PC-side: restricted to the curated PC firm list.

Table A1: Layer-1 bank-side title exclusions

Category	Excluded title keywords
Manual / service / facility labor	security guard, loss prevention, patrol officer, sergeant, bus driver, truck driver, delivery driver, chauffeur, courier, janitor, custodian, cleaner, housekeeper, porter, groundskeeper, electrician, plumber, carpenter, welder, hvac, warehouse worker, forklift, cashier, barista, server, waiter, waitress, bartender, cook, chef, kitchen, food service, valet, concierge, hostess, greeter, seafood
Creative / content / media	technical writer, copywriter, copy editor, content writer, content creator, content manager, content strategist, graphic designer, web designer, ux designer, ui designer, product designer, illustrator, animator, photographer, videographer, blogger, influencer, musician, writer/editor, editorial, journalist, reporter
Social media / brand	social media, brand ambassador, brand creative, community manager
Retired / volunteer / freelance / unemployed	retired, retiree, unemployed, job seeker, volunteer, freelance
Academic / student / teacher	phd student, graduate student, undergraduate, student leader, student ambassador, teacher, professor, lecturer, substitute teacher, tutor

continued on next page

Table A1 continued from previous page

Category	Excluded title keywords
Health / clinical / family services	nurse, nursing, cna, caregiver, medical assistant, pharmacist, paramedic, emt, dentist, physician, therapist, veterinarian, personal trainer, fitness, yoga, nanny, babysitter, au pair, dog walker, lifeguard
Interns / summer hires	intern, interns, internship, summer analyst, summer associate, summer intern
Retail / branch banking	teller, head teller, lead teller, universal banker, relationship banker, personal banker, private client banker, small business banker, banking center manager, branch manager, banking center, café ambassador, digital ambassador, ai ambassador, licensed banker, financial center manager, client service representative

Notes: Title regex applied to the lowercased `title_raw`. Any substring match drops the position from the credit-relevant (Layer-1) bank sample. Categories are not mutually exclusive; a single title may hit multiple rows. The PC-side analog of Layer 1 is the curated PC firm list rather than a title exclusion regex.

Layer 2 (subsample for the bank-to-PC movers analysis)

A bank position passes Layer 2 if it passes Layer 1 *and* matches at least one of: the description-based function classifier, a Layer-2 substring keyword (Table A2), or a Layer-2 title pattern (Table A3).

Table A2: Layer-2 substring keywords

PC-side and bank-side (both)	credit, debt, lending, lender, loan, lease, leasing, cashflowbased, cf-based, assetbased, specialtyfin, mezzanine, specialist, distress, opportunistic, opportunitistic, leverage, highyield, businessdevelopmentco
Bank-side only (added)	leveragedfinance, levfin, syndicatedlending, syndicatedloan, debtcapitalmarkets, dcm, structuredfinance, creditrisk, creditanalyst, underwriter, underwriting, fixedincome, investmentgrade, subordinated, abs, mbs, clo, cdo

Notes: Layer-2 substring keywords applied at the position level after the Layer-1 scope filter. Keywords are matched against the normalized (lowercased, whitespace- and hyphen-stripped) concatenation of company name, job title, and description, so "leveraged finance" and "Leveraged-Finance" both match the canonical keyword "leveragedfinance". The PC-side filter uses only the first row (identical on bank and PC sides); the bank-side filter uses both rows. A position passes Layer 2 if any one keyword on the applicable side appears as a substring of the normalized text.

Table A3: Layer-2 title patterns (bank-side)

Category	Title keywords (must contain)
Qualified credit roles	credit officer, credit analyst, credit manager, credit underwriter, credit associate, credit director, credit portfolio, credit administ., credit approval, credit adjudicat., head of credit, credit lead; senior credit, chief credit, sr credit, svp credit, vp credit; loan officer, loan analyst, loan underwriter, loan associate, loan director, loan manager, loan administ., loan portfolio, loan origination, loan workout, loan approval, loan head, loan lead; senior loan, chief loan, sr loan; lending officer, lending analyst, lending manager, lending director, lending associate, lending head, lending origination, lending lead; commercial lending, corporate lending, middle-market lending, specialty lending; vp lending, vice president lending, director lending, head lending, svp lending; commercial underwriting, corporate underwriting, c&i underwriting, cre underwriting; leveraged finance, lev fin, leveraged loan; loan syndication, syndicated loan, loan capital markets; specialty finance, asset-based lending, asset-based loan, asset-based finance; mezzanine, mezz debt, mezz finance, mezz loan, mezz associate, mezz analyst; direct lending; distressed debt, distressed credit, distressed loan; workout officer, workout specialist, workout manager, workout analyst; special assets
Investment-banking advisory	investment banking; ib analyst, ib associate, ib vp, ib vice president, ib director; m&a; mergers and acquisitions; equity capital markets; ecm analyst, ecm associate, ecm origination; investment banker; corporate finance analyst, corporate finance associate, corporate finance vp, corporate finance director, corporate finance head; sector coverage, coverage banker; healthcare investment banking, tmt investment banking, fig investment banking, consumer investment banking, industrials investment banking, energy investment banking, technology investment banking, media investment banking, telecom investment banking, real estate investment banking, natural resources investment banking
Markets / treasury / quant	sales and trading; equity trader, equity sales, equity trading; fixed-income trader, fixed-income sales, fixed-income trading; bond trader, bond sales, bond trading; fx trader, fx sales, fx trading; rates trader, rates sales, rates trading; commodities trader, commodities sales, commodities trading; trading analyst, trading associate, trading director; trader; treasury analyst, treasury associate, treasury manager, treasury director, treasurer; quantitative analyst, quantitative associate, quantitative researcher, quantitative developer, quantitative trader, quantitative strategist; quant analyst, quant trader, quant associate, quant strategist, quant researcher

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Table A3 continued from previous page

Category	Title keywords (must contain)
Title exclusions	credit card, consumer credit, credit counselor, credit collector, credit investigator, retail credit, home loan, home lending, home equity, mortgage, consumer loan, consumer lending, auto loan, sba, loan processor, loan processing, loan documentation, loan doc, loan servicing, loan closer, loan coordinator, loan operations, loan support, loan assistant, securities lending, securities loan, stock loan, insurance, field underwriting, tax credit, student loan, fha, usda, va loan

Notes: Bank-side only; regex applied to the lowercased `title_raw`. The first three categories (qualified credit roles, investment-banking advisory, markets/treasury/quant) are positive triggers; the last category is an exclusion overlay (e.g., "credit card associate" is downgraded because it matches "credit card" in the exclusion list even though "credit" is a positive substring). The description-based function classifier (covering direct-lending, senior, junior, distressed, opportunistic, ABL, cash-flow lending, structured, revolver, and capital-markets-credit sub-flags) is an independent positive trigger. A position counts as Layer-2 credit-relevant if the description classifier fires, the substring keyword list in Table A2 matches, or any of the three positive title-pattern categories matches and the title is not in the exclusions row.

A.2.1 PC sample primary filter (who counts as a PC employee)

A worker at a candidate PC firm enters the PC sample if at least one of three rules holds for that worker–firm pair in the order of priority.

- **Share rule.** The firm's PC fund-size share (PitchBook) and PC role share (Preqin) jointly indicate that PC is the dominant activity:
  1. if the firm is in both PitchBook and Preqin, the share rule fires when the PitchBook PC share ≥ 0.5 *and* the Preqin private-debt share ≥ 0.5;
  2. if the firm is in PitchBook only, it triggers when the PitchBook PC share ≥ 0.5;
  3. if the firm is in Preqin only, it triggers when the Preqin private-debt share ≥ 0.5.

  The PitchBook PC share is computed at the entity level (PC fund size divided by total PC + PE + VC fund size), not rolled up to the parent. Classifying private credit at the entity rather than the parent level mitigates over-counting of private credit employees in cases where a private credit firm is owned by a large insurance parent. When the share rule is triggered, every employee at the firm is counted as a PC employee (e.g., Ares, Barings, TCW Group).

- **BDC rule.** The firm is a publicly listed Business Development Company. Every employee at a BDC is counted as a PC employee, unconditionally.

- **Keyword rule.** The worker's job title, company name, or description (concatenated and normalized for whitespace and hyphens) contains any of the credit-relevant substring keywords listed in Table A4 below. This rule selectively retains credit-active workers at multi-strategy alternative asset managers (e.g., Blackstone, Apollo, KKR) where the firm-level PC share is below 50%.

A worker–firm pair is in the PC sample if any one of the three rules fires. All counts of PC firms and PC employees reported in the paper (Table 1, the bank-to-PC mover panel in Section 3.2) condition on this keep rule.

Table A4: PC-keep keyword rule

Category	Substring keywords (any match triggers the rule)
Generic credit / debt / lending	credit, debt, lending, lender, loan
Asset class / collateral	lease, leasing, cashflowbased, cfbased, assetbased, specialtyfin
Mezzanine / distressed / opportunistic	mezzanine, distress, opportunistic, opportunitistic
Leveraged / high-yield / specialist	leverage, highyield, specialist
Business Development Company	businessdevelopmentco

Notes: Substring keywords applied to the lowercased, whitespace- and hyphen-stripped concatenation of company name, job title, and description, so "leveraged finance" and "Leveraged-Finance" both match the canonical keyword "leverage". Matching is a plain substring test (e.g., "credit" fires on "private credit", "credit analyst", and "creditor"). At a candidate PC firm, a worker–firm pair is retained in the PC sample if any keyword in this table appears in the worker's normalized text. This rule is one of three (share rule, BDC rule, keyword rule) in the PC primary filter and is the only one used to selectively retain credit-active workers at multi-strategy firms whose overall PC share is below 50%.

A.3 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 first restrict the sample to U.S.-based positions and remove roles that are clearly unrelated to lending or investment activity. 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 are:

- *Sourcing*: deal origination, client relationship management, and capital raising;
- *Screening*: initial evaluation and due diligence;
- *Underwriting*: credit structuring and documentation;
- *Approval*: credit committee review and compliance;
- *Risk management*: portfolio risk assessment;
- *Monitoring*: ongoing loan surveillance and workouts.

The exact keyword stems are listed in Table A5; a position is assigned to function x if its lowercased description contains any stem in row x as a substring. The six narrow indicators are not mutually exclusive — a description that mentions both "credit committee" and "risk management" is counted in both Approval and Risk management.

Table A5: Function-classifier keyword stems (applied to the lowercased job description).

Function	Keyword stems (any substring match in the description)
Sourcing	origination, originat, deal originat, deal-originat, relationship, sourcing, deal sourcing, deal-sourcing, sourcing investment, client, customer, sales, capital raising, builds relationship, builds relationships, build close relationship, procured, managed client relationships, implemented new clients
Screening	screen, diligence, analy, research
Underwriting	underwrit, underwriting, underwrot, structuring, negotiat, memorand, draft, bespoke
Approval	investment committee, credit committee, loan committee, review, review committee, compliance, approv, loan processing, final review, verif, reconc, credit approval, accounting diligence
Risk management	risk assess, assess risk, managing their risk, managing risk, mitigate risk, mitigate the risk, managed market risk, managed the market risk, risk management, migrating risk, risk committee
Monitoring	amend, modif, renegotia, workout, monitor, monitoring, covenant, oversight, oversaw, oversee, overseeing

Notes: A position is assigned to function x if its lowercased description contains any stem in row x as a substring. Stems are intentionally short (e.g., "originat" catches origination, originated, originating) and are not whitespace-bounded; this trades some false positives at the margin (e.g., "analy" catches "analysis") for higher recall on the often-terse LinkedIn descriptions. Workers with no description (about 50% of bank-side observations) are unclassified by construction.

For parsimony in our regression analyses, we aggregate the six narrow functions into three broad categories. *Sourcing* retains the narrow sourcing classification. *Diligence* combines screening, underwriting, and monitoring. *Risk/Approval* combines risk management and approval. A position is assigned to a broad function if it belongs to any of the constituent narrow functions. The broad categories are not mutually exclusive.

Figure A1 illustrates the effect of each filter on sample size, separately for banks and PE/PC lenders.

A.4 Hierarchy measure construction (layers and shape)

We measure each firm's organizational hierarchy using a four-stage pipeline that follows Ewens and Giroud (2025) with two computational substitutions (closed-form SpringRank in place of Minimum Violation Ranking; AIC-based GMM for layer-count selection in place of k-means with a rank-uncertainty rule). Both substitutions preserve the substantive Ewens-Giroud identification: layers emerge from rank clusters in the within-firm role-to-role transition graph, not from external seniority inputs. Mean Revelio seniority increases monotonically across the recovered layers (cross-check; not used in clustering).

Stage 1: Canonical roles. For each firm we map raw job titles to a canonical role taxonomy. Titles are lower-cased, stripped of leading/trailing punctuation, and matched against a manual rules list (e.g., "Senior Vice President of Lending" $\rightarrow$ canonical role `vp_lending`). Titles that fail to match any rule are dropped from the hierarchy build.

Stage 2: Internal labor market. For each firm we identify the largest connected component ("largest internal labor market", or ILM) of the role $\rightarrow$ role transition graph, where an edge $r \rightarrow r'$ records that at least one worker held canonical role r at the firm and subsequently held role r' at the same firm. Edge weights are person-years of transition observations. Restricting to the largest ILM ensures that the rank estimation operates on a single connected sub-graph and avoids isolated roles.

Stage 3: Ranks and number of layers. On each firm's largest ILM:

- **Ranks (SpringRank).** We solve the SpringRank quadratic energy via a sparse linear system to obtain a real-valued rank for every role. The energy minimizes weighted violations of the transition direction on the role graph; equivalently, it minimizes $\sum_{r \to r'} w_{rr'}(s_r - s_{r'} - 1)^2$ where s_r is role r's rank and $w_{rr'}$ is the edge weight. Bootstrap standard errors are obtained by Poisson-resampling edge weights 30 times and recomputing the rank vector. An anchored variant adds a small per-node penalty $\lambda_r(s_r - \bar{s}_r)^2$ pulling each role toward its mean-rank anchor.
- **Number of layers K (Gaussian-mixture AIC).** We fit a 1-D Gaussian-mixture model to the firm's rank distribution for $K \in [K_{\min}, 15]$, where $K_{\min} = \max(2, \lceil \log_2 n_{\text{roles}} \rceil)$ is a structural floor that prevents AIC from collapsing large firms (> 400 roles) to $K = 2$ due to the bimodal junior/senior density. The AIC-minimizing K is the firm's recovered layer count. A post-hoc layer-thinning step merges any layer with fewer than two distinct roles into its nearest neighbor.

Stage 4: Firm-year aggregation and depth index. For each $(firm, year)$ we compute the share of unique workers in each recovered layer, the number of populated layers in that year, and the year-specific hierarchization measure $H = 1 - \sum_k \beta_k^2$. The continuous *hierarchical depth index* is a z-scored composite of K, H, and the top-layer worker share averaged over years; it is used in Section 4.2 to break ties among the largest firms that saturate at the layer-count cap.

Shape: pyramid plots. The firm-year shares are used to construct the *hierarchy pyramids* (Figures B1a and 6). For each firm we map the recovered layer $k \in \{1, \ldots, K\}$ to a within-firm relative position k/K, then bin into either five quintile buckets or three coarse layers (junior 1–2, mid 3–4, senior 5–7 for the seven-level Revelio cut; or bottom/middle/top for the three-layer cut). Within each firm the layer shares sum to 1; the pyramid figure displays the firm-weighted average share at each bucket, separately for banks and PC firms.

A.5 Seniority measures (quintile, dummy, implied years)

Beyond the Revelio SOC seniority level $s \in \{1, \ldots, 7\}$ that we use as the main outcome in the career-mobility regressions, we construct three alternative seniority measures used in the appendix robustness tables (Table 4 and the alt-measures event studies).

Senior-role indicator. A cross-firm-comparable title-keyword indicator that does not depend on K: it equals 1 if the worker's title matches one of the senior-investment patterns (Managing Director, Partner, Principal, Director, Head of, Chief X Officer) listed in Section A.2, with the standard exclusions (AVP, associate director, retail / service partner, etc.). Because the dummy does not shrink with K, it is useful as a robustness outcome when the continuous within-firm share is mechanically inflated by sparse-K destination firms.

Implied years. To put seniority effects on an interpretable "years of bank-career equivalent" scale, we calibrate two lookups on the pre-treatment bank-worker sample (bank employees in 2008–2012):

- $f(k)$ = mean total experience among pre-treatment bank workers at Revelio seniority $k \in \{1, \ldots, 7\}$. The implied-years outcome for each person-year is $f(s_{i,t})$.
- $f(d)$ = mean total experience among pre-treatment bank workers at senior-role-dummy $d \in \{0, 1\}$. The corresponding outcome is $f(d_{i,t})$.

We also estimate a within-bank variant $f(k, b)$ for each origin-bank b and use it when available, falling back to the pooled $f(k)$ otherwise. Both implied-years measures are leave-one-out at the (worker, seniority-level) cell, so a worker's own pre-treatment experience does not enter their own calibration.

The IV / OLS coefficients on the implied-years outcome read directly as years of additional bank-career advancement that compliers experience from moving to PC.

A.6 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.6.1 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.6.2 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.6.3 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.6.4 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:

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

   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.6.5 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.

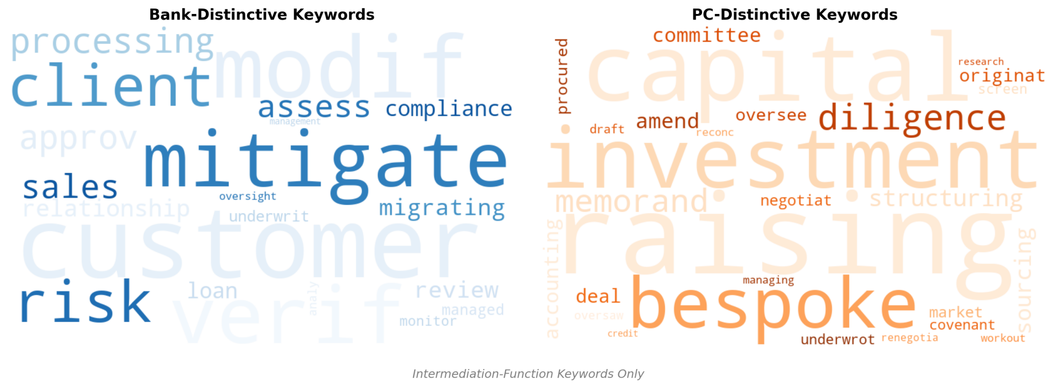
We develop a rule-based natural language processing pipeline to extract covenant provisions from the full text of credit agreements. For negative covenants, we extract six categories of negative covenants commonly found in credit agreements: limitations on liens, indebtedness, investments, restricted 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.

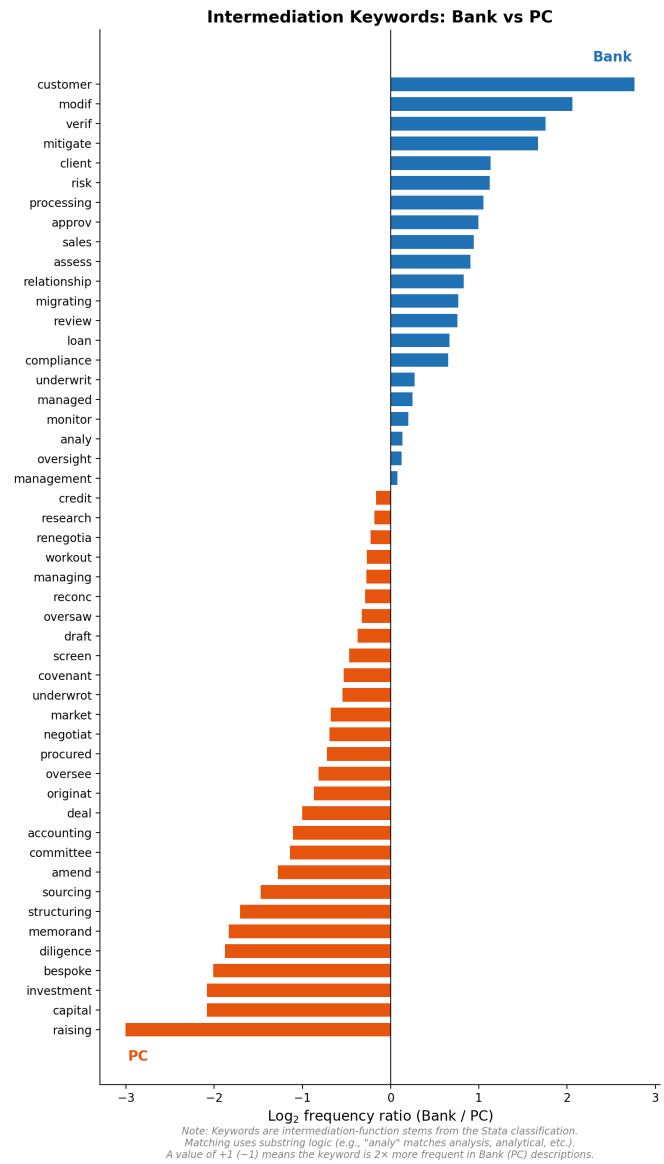
For affirmative covenants, we extract six categories: quarterly financial statements, annual financial statements, annual projections/budgets, monthly financial statements, lender meetings/conference calls, and board observation rights. For each affirmative covenant type, we define required keyword groups 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.6.6 Additional results on contract terms

Figure A2: Intermediation keywords: Bank vs. PC



(a) Differential word cloud

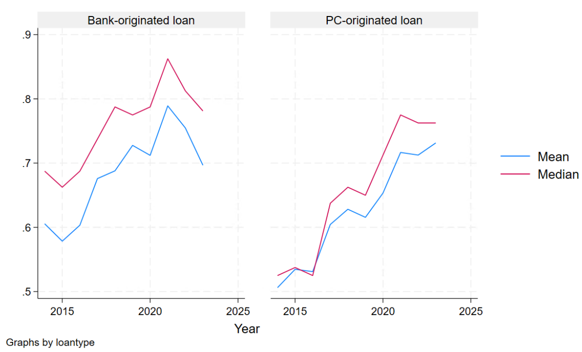


(b) Log frequency ratio (bank/PC)

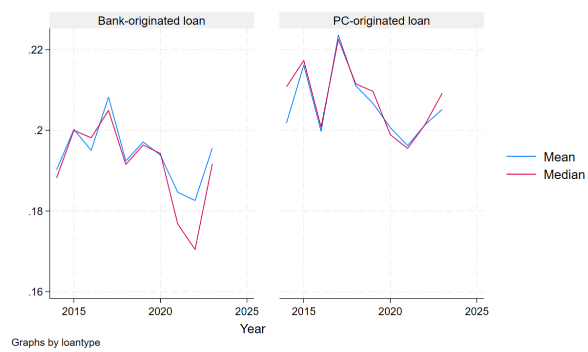
Notes: Intermediation-function keywords in job descriptions, bank versus PC. Panel (a): differential word cloud—word size reflects the degree of overrepresentation ($\log_2$ frequency ratio) in that lender type. Panel (b): $\log_2$ frequency ratio (bank/PC) for each intermediation-function keyword stem; a value of $+1$ (-1) indicates the keyword is twice as frequent in bank (PC) job descriptions.

Figure A3: Extensive measures of customization for bank and non-bank contracts

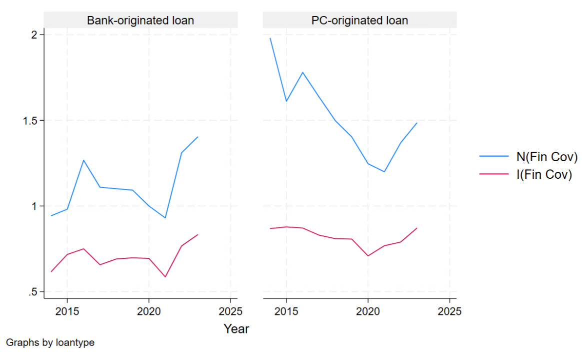
Panel A: Proportion of Boiler Plate Terms in Contract



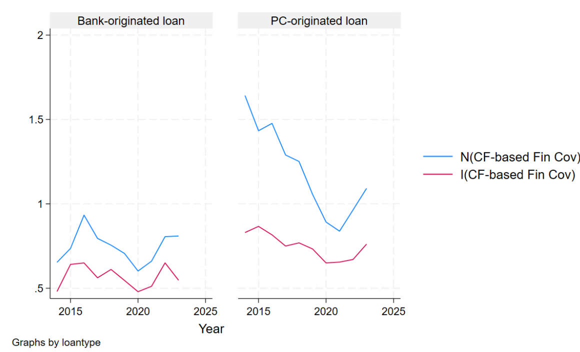
Panel B: Proportion of contract terms in boiler plate



Panel C: Number of financial covenants



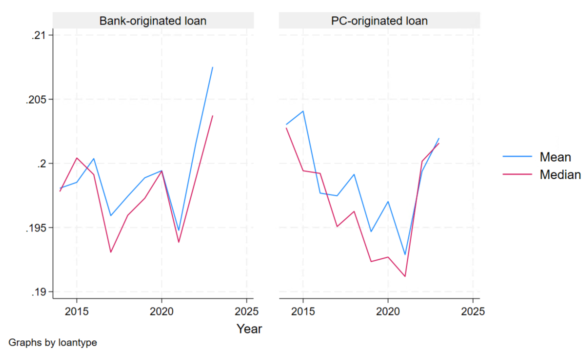
Panel D: Number of cash flow financial covenants



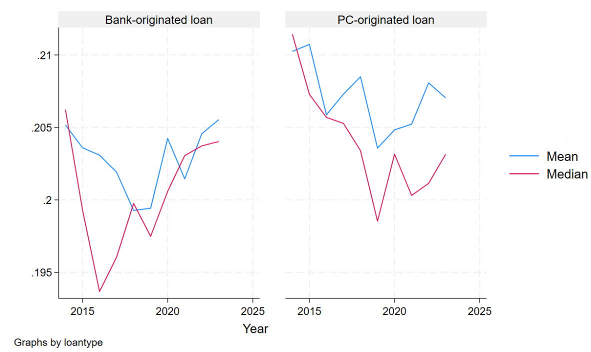
Notes: This figure compares extensive measures of customization between PC-originated and bank-originated loans. Panels A-D show the mean and median for proportion of boiler plate terms in contract (Panel A), proportion of contract terms in boiler plate (Panel B), number of financial covenants (Panel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

Figure A4: Negative Covenants for bank and non-bank contracts

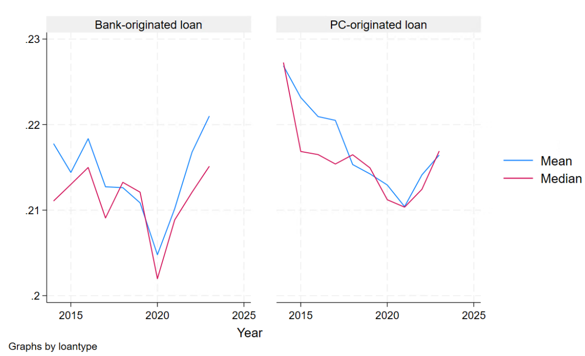
Panel A: Lien



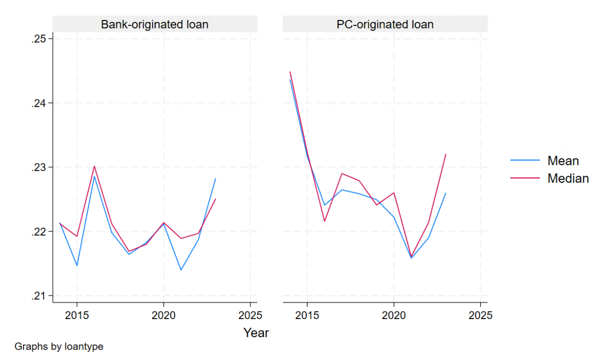
Panel B: Indebtedness



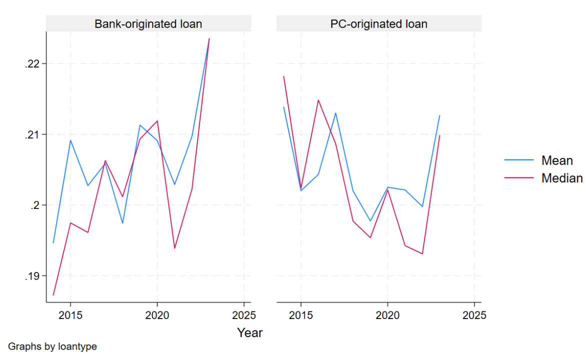
Panel C: Investment



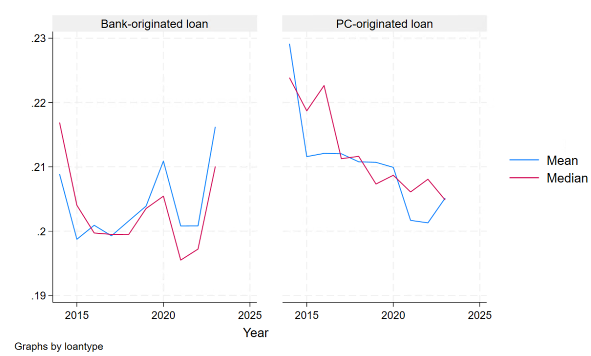
Panel D: Payment



Panel E: Asset sale



Panel F: Fundamental change

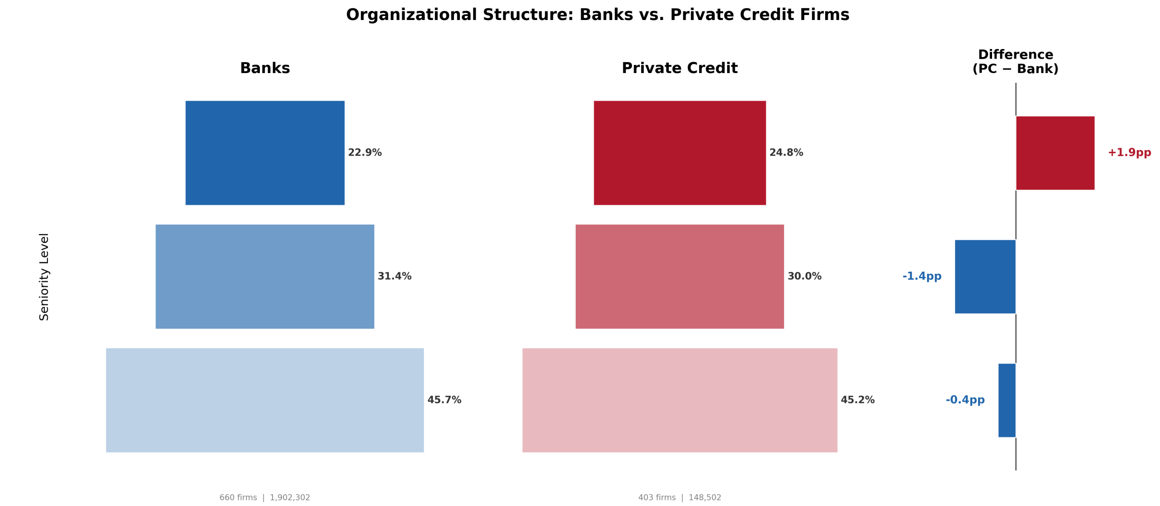


Notes: This figure compares various measures of negative covenants between PC-originated and bank-originated loans. Panels A-F show the mean and median for lien, indebtedness, investment, payment, asset sale, and fundamental change.

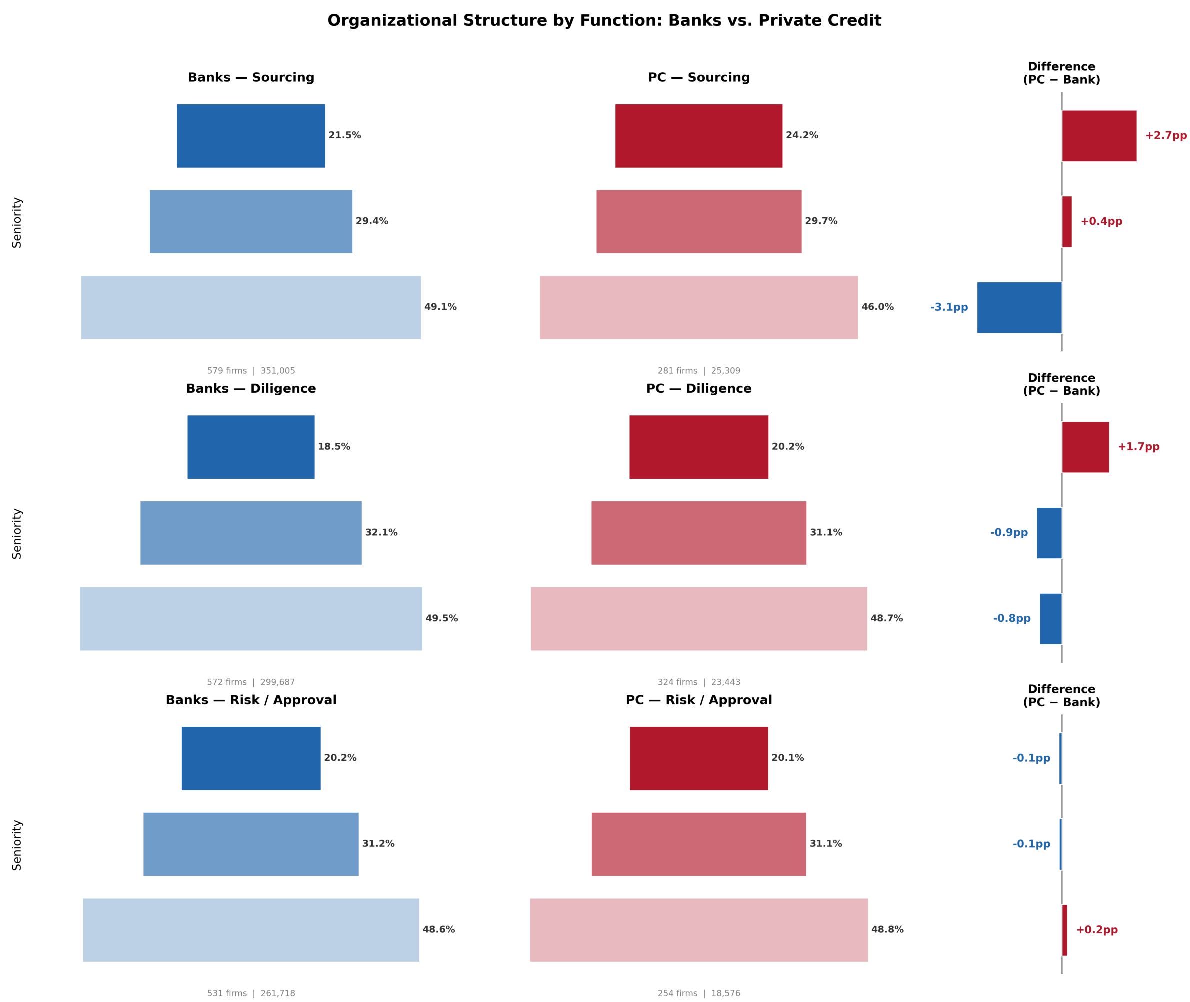
B Additional Figures and Tables

B.1 Figures

Figure B1: Organizational structure: Banks vs. private credit firms (Revelio seniority)



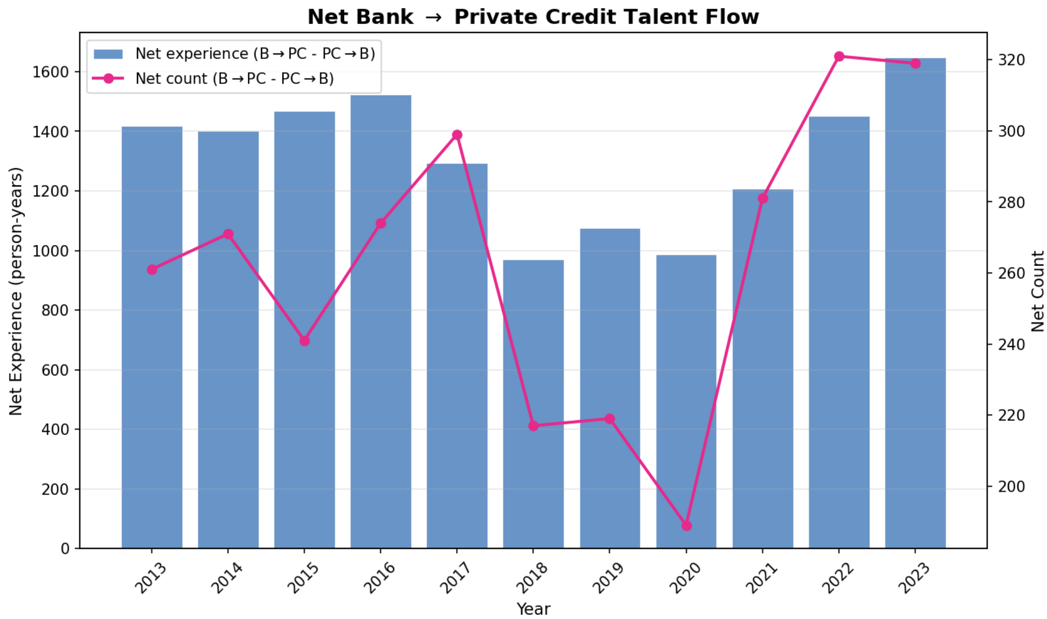
(a) Overall



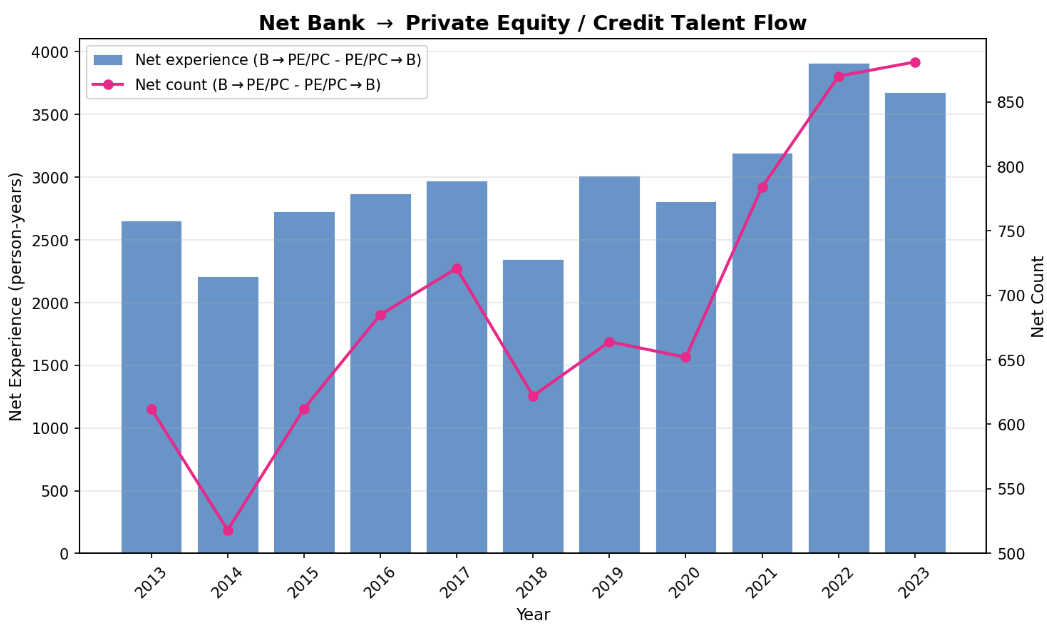
(b) By function

Notes: Share of employees at three seniority tiers (Junior: levels 1–2; Mid: levels 3–4; Senior: levels 5–7) based on Revelio seniority classifications. Panel (a) is overall; Panel (b) splits by function (sourcing, diligence, risk/approval). The right column shows the difference (PC − Bank) in percentage points. Diligence exhibits the largest structural gap, with banks concentrating diligence workers at junior levels while PC firms employ more mid-level and senior diligence staff. The sample includes all bank and PC employees from 2012 to 2023.

Figure B2: Net flow of talent from banks to private capital firms



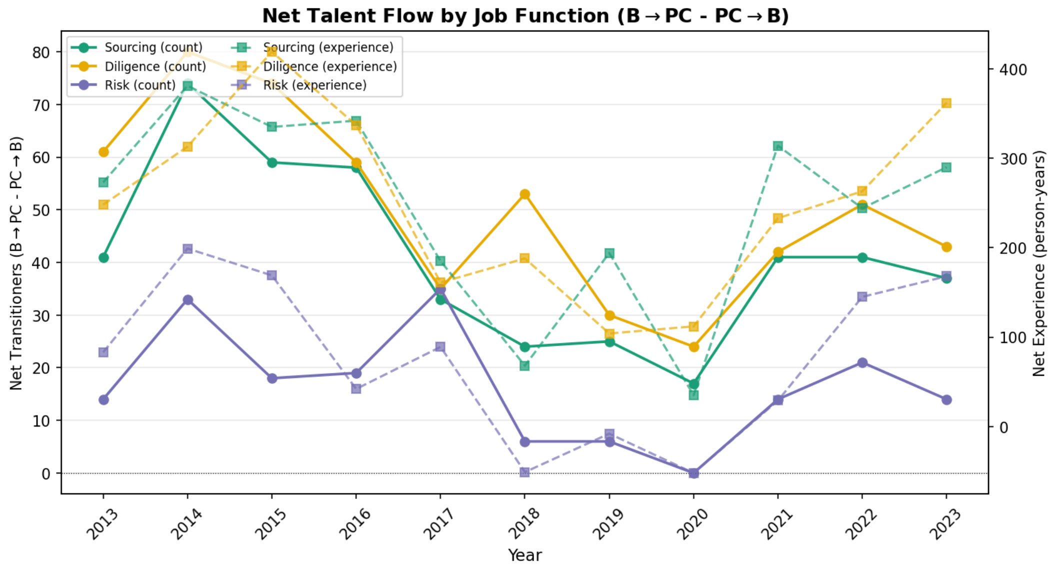
(a) Private credit (PC)



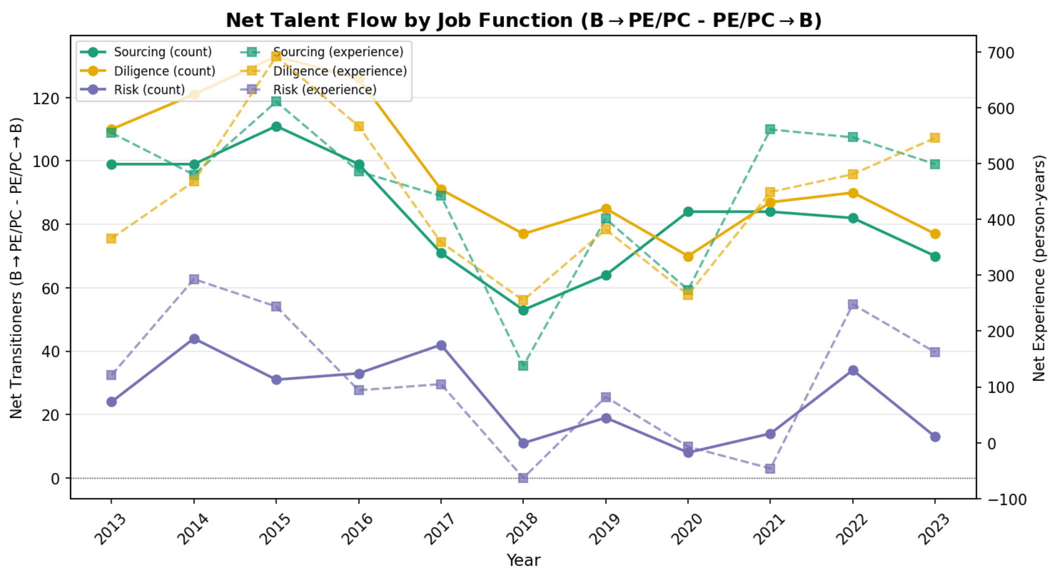
(b) Private equity / private credit (PE/PC)

Notes: Net flow of talent from banks to private capital firms by year (bank→nonbank minus nonbank→bank). Panel (a) is private credit (PC); Panel (b) is PE/PC (private equity and private credit). Bars show net experience in person-years (left axis); the line shows the net headcount of transitioners (right axis). Data are from Revelio Labs matched to PitchBook lenders, 2013–2023.

Figure B3: Net outflows from banks to private capital firms by function



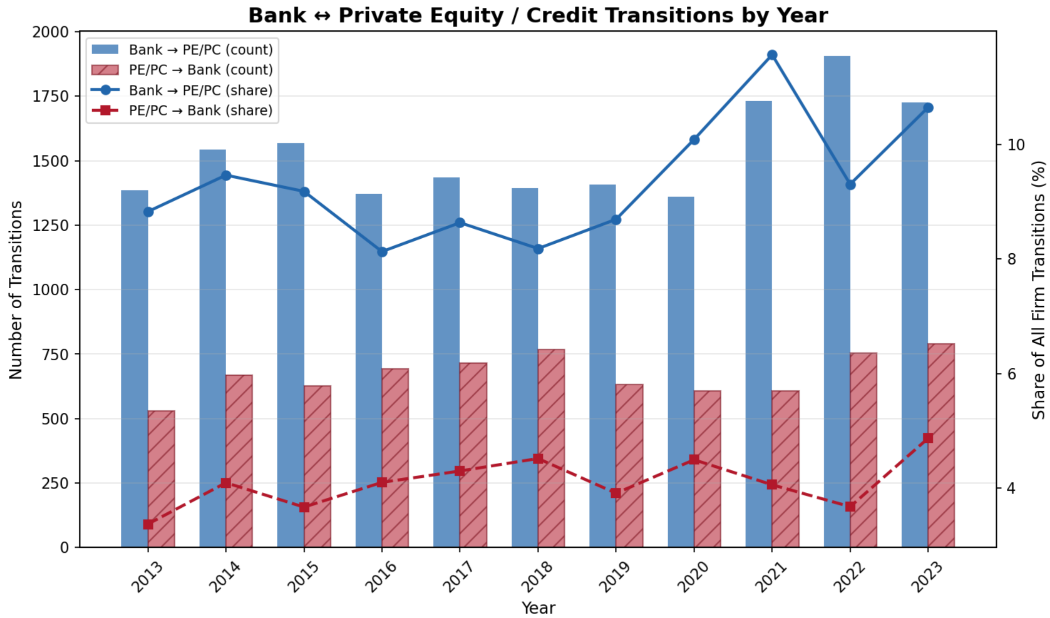
(a) Private credit (PC)



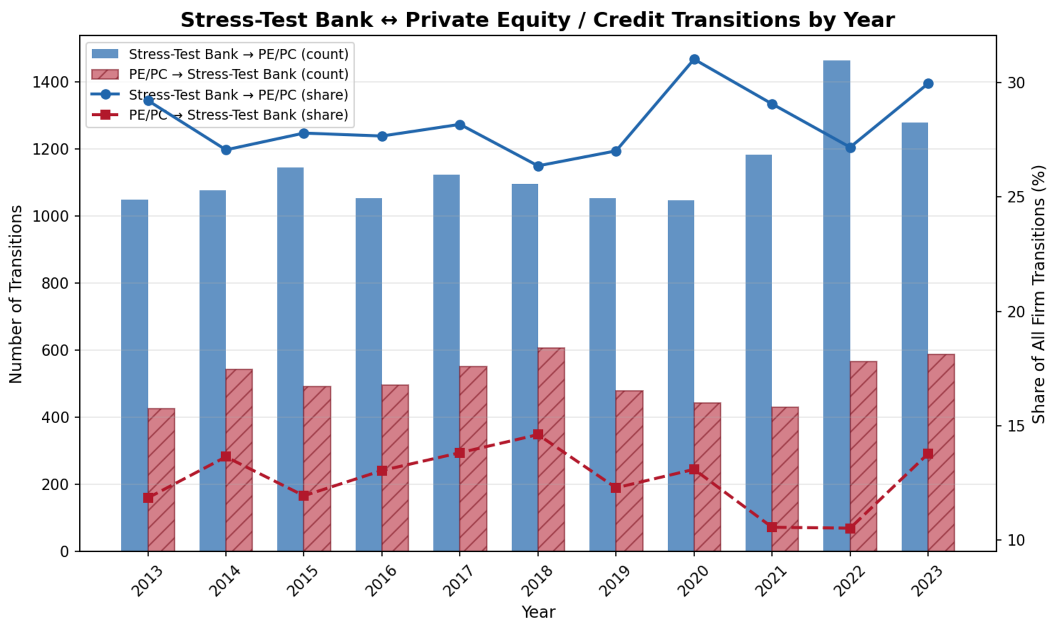
(b) Private equity / private credit (PE/PC)

Notes: Net outflows by function (sourcing, diligence, risk/approval), 2013–2023. Panel (a) is private credit (PC); Panel (b) is PE/PC. Solid lines show net headcount flow (left axis); dashed lines show net cumulative experience flow in person-years (right axis). Net outflow is bank→nonbank minus nonbank→bank. Data are from Revelio Labs matched to PitchBook lenders.

Figure B4: Transitions between banks and PE/PC firms



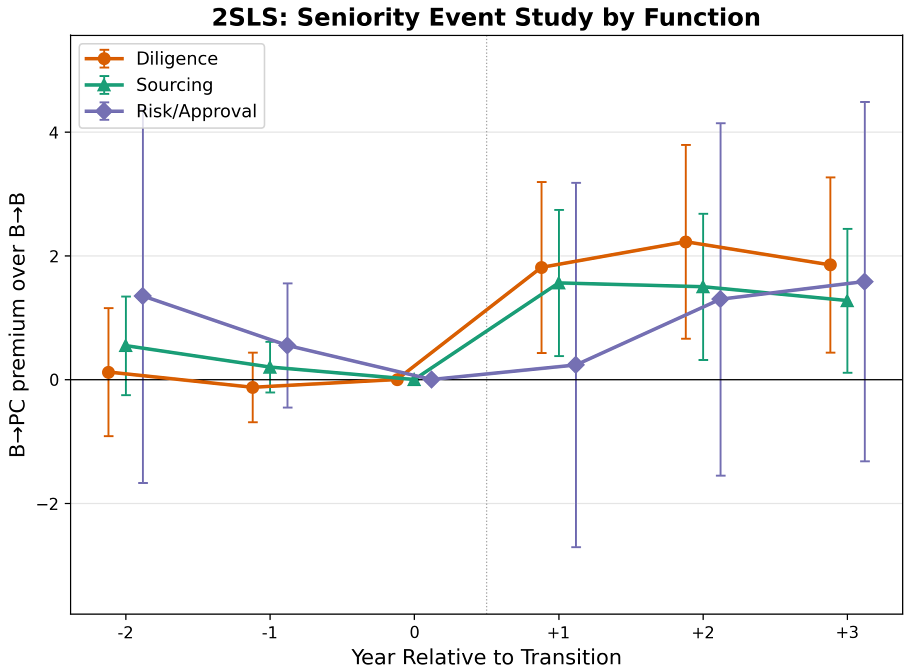
(a) All banks (no Layer-2 filter)



(b) Stress-test banks (IV sample)

Notes: This figure shows the number of job transitions between banks and PE/PC firms in each year from 2013 to 2023. Panel (a) includes all banks with no Layer-2 (strategic-credit) filter; Panel (b) restricts the bank side (both directions) to the DFAST stress-test banks used to construct the Bartik instrument—the same bank universe as the IV sample (Layer-2 filter retained). Bars show transition counts (left axis); lines show each direction's share of all employer-to-employer moves, including bank-to-bank, PE/PC-to-PE/PC, bank-to-PE/PC, and PE/PC-to-bank transitions (right axis). PE/PC includes both private equity and private credit firms. Data are from Revelio Labs matched to PitchBook lenders, 2013–2023.

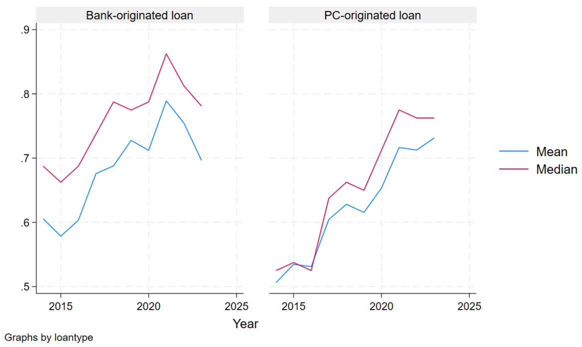
Figure B5: 2SLS event study by function



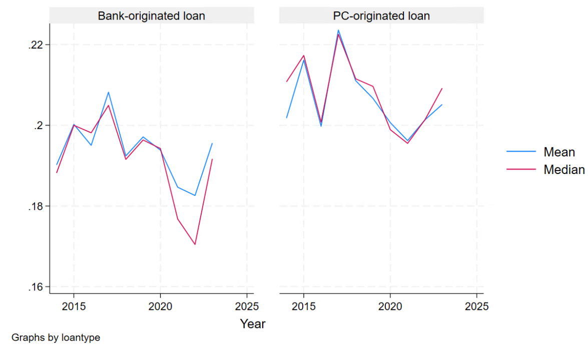
Notes: Seniority premium for bank→PC movers, split by pre-move function at the origin bank. Same specification as Figure 3. 99% confidence intervals, clustered at the bank × year level.

Figure B6: Extensive measures of customization for bank and nonbank contracts

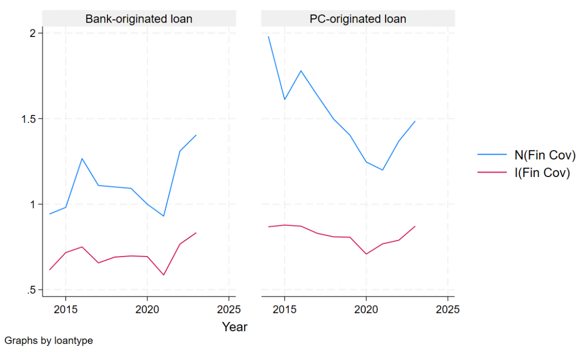
Panel A: Proportion of Boiler Plate Terms in Contract



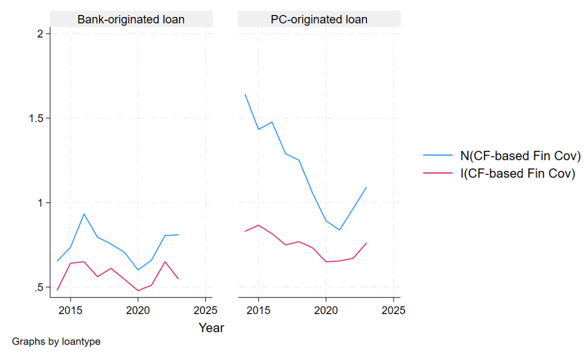
Panel B: Proportion of contract terms in boiler plate



Panel C: Number of financial covenants



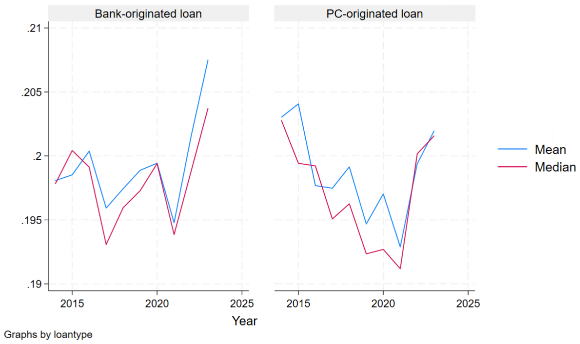
Panel D: Number of cash flow financial covenants



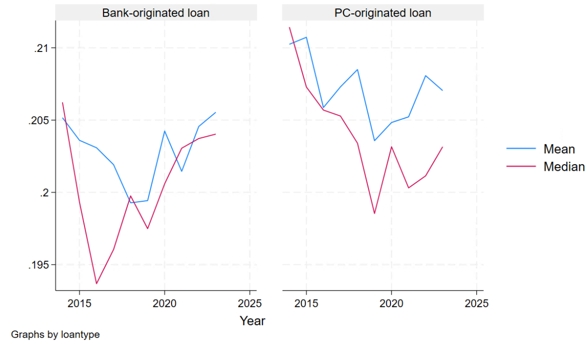
Notes: This figure compares extensive measures of customization between PC-originated and bank-originated loans.

Figure B7: Negative Covenants for bank and nonbank contracts

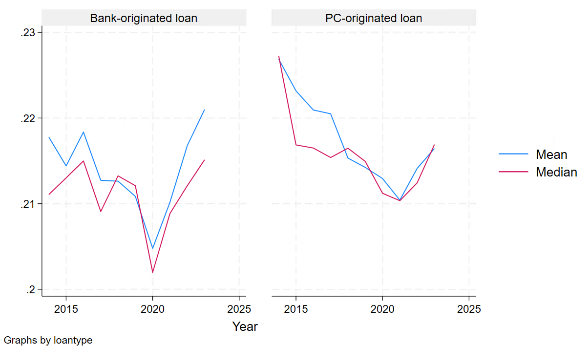
Panel A: Lien



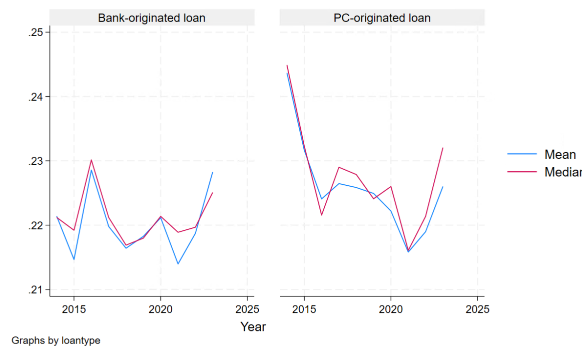
Panel B: Indebtedness



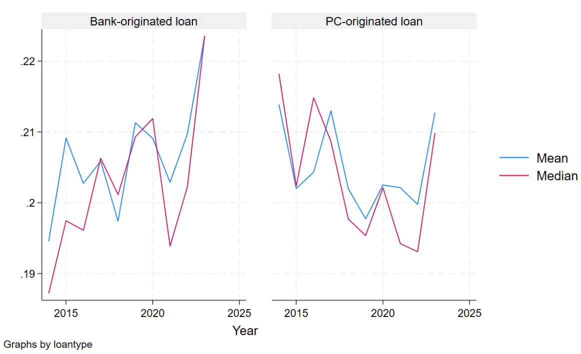
Panel C: Investment



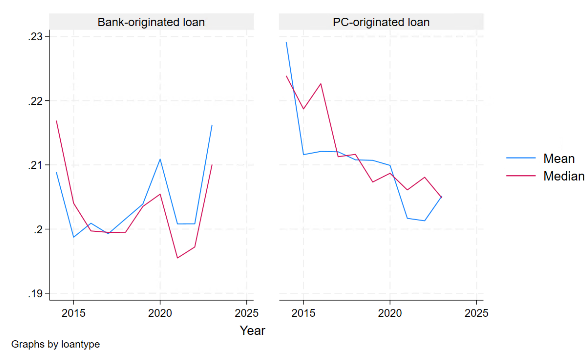
Panel D: Payment



Panel E: Asset sale

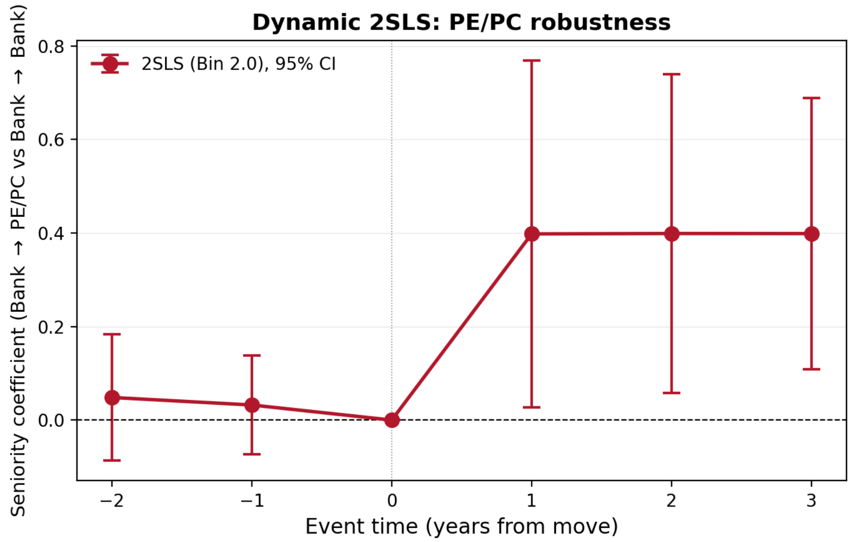


Panel F: Fundamental change

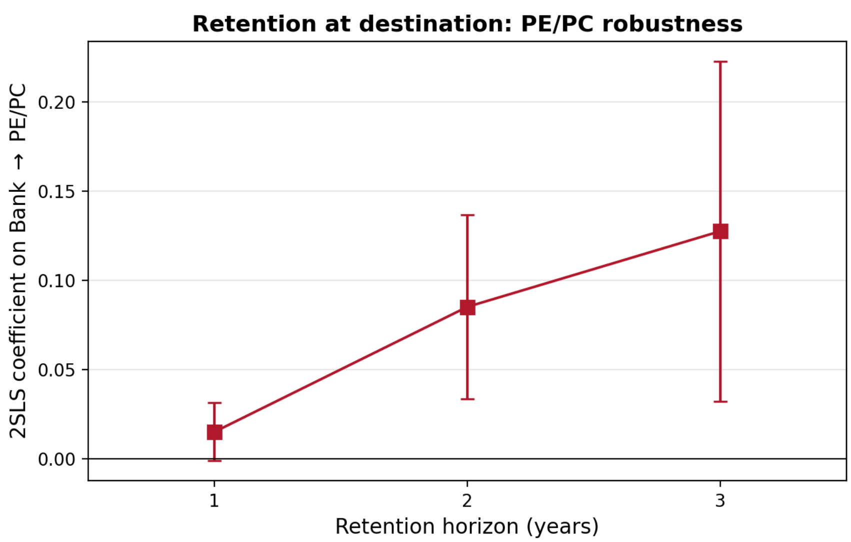


Notes: This figure compares various measures of negative covenants between PC-originated and bank-originated loans.

Figure B8: Robustness: bank→PE/PC movers



(a) 2SLS seniority event study



(b) 2SLS retention at destination

Notes: Robustness for bank→PE/PC movers, with the treatment redefined to include both PE and PC destinations and the Bartik share computed over PE/PC leavers. Panel (a): dynamic 2SLS seniority event study, same specification as Figure 3 (bank→PE/PC event-time indicators instrumented by their Bartik interactions; controls for event-time indicators and total experience; user and year fixed effects), 95% confidence intervals. Panel (b): 2SLS retention at the destination firm at horizons $t+1$ to $t+3$. Both panels cluster at the bank × year level.

B.2 Tables

Table B1: Top 10 Banks by Average Annual Headcount

Firm	# of Employees/Year	Employee Share
1. Bank of America Corp.	80,376	11.6%
2. Wells Fargo & Co.	78,818	11.4%
3. JPMorgan Chase & Co.	73,444	10.6%
4. Citigroup, Inc.	38,030	5.5%
5. Morgan Stanley	32,830	4.8%
6. Capital One Financial Corp.	26,352	3.8%
7. The PNC Financial Services Group, Inc.	24,362	3.5%
8. The Goldman Sachs Group, Inc.	20,391	3.0%
9. UBS Group AG	19,968	2.9%
10. The Charles Schwab Corp.	16,210	2.3%

Notes: This appendix table lists the top 10 banks (Revelio ultimate-parent level) by average yearly headcount over 2013–2023, mirroring Panel C of Table 1. The sample is restricted to bank positions surviving the credit-role keep filter (job titles or descriptions tagged as credit-, lending-, or debt-related), the same broad firm-level bank sample used throughout the paper. Subsidiary banks (e.g., Bank of America, N.A.) are folded into their ultimate parent (Bank of America Corp.). *# of Employees/Year* is the mean across years of unique LinkedIn user-positions at the parent in a given year, restricted to credit-relevant positions as defined above; *Employee Share* divides this by the same total summed across all bank parents in the sample, and so represents each bank's share of total credit-relevant bank headcount in the panel.

Table B2: Pre-move characteristics of bank leavers

	Bank → Bank		Bank → PC		
	Mean	SD	Mean	SD	Diff
Seniority	3.314	1.458	3.006	1.372	-0.308***
Total experience (years)	7.100	6.450	4.626	5.376	-2.474***
Sourcing experience	2.821	4.671	0.973	2.876	-1.847***
Diligence experience	2.006	3.700	0.797	2.396	-1.209***
Risk control experience	1.916	3.839	0.486	1.943	-1.430***
Has MBA	0.190	0.392	0.164	0.370	-0.026***
Observations	17,533		1,685		

Notes: Pre-move characteristics measured at event time $t = 0$ (last year at origin bank). Sample: stress-test bank leavers, 2013–2022. Bank → PC: movers to private credit firms (pc = 1). Bank → Bank: movers to another bank. Experience variables are cumulative years in each function at a bank. Diff column reports mean(B→PC) − mean(B→Bank). *** p<0.01, ** p<0.05, * p<0.1 from Welch's *t*-test.

Table B3: Stress test bank-years with minimum capital distance below 1.0

Bank	Year	Tier 1	Total RBC	Leverage	Min Distance
The Goldman Sachs Group, Inc.	2013	1.50	2.40	**-0.10**	-0.10
Morgan Stanley	2013	1.50	0.70	**0.50**	0.50
JPMorgan Chase & Co.	2013	1.40	1.90	**0.70**	0.70
Zions Bancorporation	2014	-0.60	**-0.80**	0.50	-0.80
Bank of America Corporation	2014	0.80	1.20	**0.40**	0.40
HSBC North America Holdings Inc.	2014	3.40	10.20	**0.40**	0.40
Morgan Stanley	2014	1.10	0.90	**0.50**	0.50
JPMorgan Chase & Co.	2014	1.10	1.30	**0.60**	0.60
The Goldman Sachs Group, Inc.	2014	1.30	1.50	**0.90**	0.90
The Goldman Sachs Group, Inc.	2015	0.40	**0.10**	1.40	0.10
Morgan Stanley	2015	**0.50**	0.60	0.50	0.50
Citigroup Inc.	2015	0.80	1.20	**0.60**	0.60
JPMorgan Chase & Co.	2015	1.30	1.60	**0.60**	0.60
The PNC Financial Services Group, Inc.	2015	0.90	**0.70**	1.50	0.70
State Street Corporation	2015	3.70	3.60	**0.80**	0.80
Huntington Bancshares Incorporated	2016	**0.30**	0.60	1.00	0.30
BMO Financial Corp.	2016	**0.40**	0.70	0.90	0.40
KeyCorp	2016	**0.80**	0.90	2.00	0.80
The PNC Financial Services Group, Inc.	2016	**0.80**	1.30	1.40	0.80
Morgan Stanley	2016	4.20	5.50	**0.90**	0.90
State Street Corporation	2017	4.40	3.50	**0.60**	0.60
Morgan Stanley	2017	5.70	6.90	**0.90**	0.90
State Street Corporation	2018	3.00	2.00	**0.20**	0.20
Morgan Stanley	2018	3.40	4.20	**0.30**	0.30
The Goldman Sachs Group, Inc.	2018	1.30	2.20	**0.40**	0.40
RBS Citizens Financial Group, Inc.	2018	**0.90**	1.40	1.90	0.90
HSBC North America Holdings Inc.	2020	1.30	3.80	**-0.80**	-0.80
BMO Financial Corp.	2020	**-0.10**	0.60	0.50	-0.10
M&T Bank Corporation	2020	**0.20**	0.50	0.90	0.20
HSBC North America Holdings Inc.	2021	3.40	6.00	**0.20**	0.20
HSBC North America Holdings Inc.	2022	3.50	4.90	**0.00**	0.00
The Goldman Sachs Group, Inc.	2022	4.00	4.60	**0.60**	0.60
Bank of America Corporation	2022	3.20	3.40	**0.80**	0.80
The Bank of New York Mellon Corporation	2022	6.40	5.30	**0.80**	0.80

Notes: Bank-years from DFAST severely adverse scenario where the minimum distance to regulatory capital thresholds falls below 1.0 percentage points. Distance is computed as the stressed capital ratio minus the regulatory minimum (Tier 1: 6%, Total RBC: 8%, Leverage: 4%). The binding ratio (smallest distance) is shown in **bold**. Negative values indicate the bank would breach the threshold under the stress scenario.

Table B4: Causal effect of moving to private credit on non-salary compensation

Dep. var.: $\Delta(total\_compensation) - \Delta(salary)$*, per leaver, in USD*

	OLS		IV bin 1.0		IV trunc 1.0	
	(1)	(2)	(3)	(4)	(5)	(6)
Bank → PC	27874***	30924***	124800*	135822**	146784*	156643*
	(6565)	(6537)	(68535)	(68330)	(84929)	(84563)
KP F-stat			29.3	28.0	31.4	30.3
Observations	34,281	34,281	34,281	34,281	34,281	34,281
Mean dep. var.	25,777	25,777	25,777	25,777	25,777	25,777

Standard errors in parentheses, clustered at the origin-bank × event-year level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Notes: Long-difference per-leaver OLS and 2SLS comparing bank-to-PC movers (treatment) with bank-to-bank movers (control) among stress-test bank leavers. Sample is the per-leaver long-difference panel of bank leavers during 2013–2022. The dependent variable is Δ(total compensation) $-$ Δ(salary) in USD, computed at the position-transition step: pre-period = end of last position at the origin bank; post-period = start of first position at the destination firm. Both pay series are Revelio position-level imputations; the difference proxies bonus and equity / carried-interest pay. *Bank → PC* = 1 if the destination is private credit, 0 if another bank. Columns (1)–(2) report OLS estimates; columns (3)–(6) report 2SLS estimates in which the *Bank → PC* indicator is instrumented with the Bartik IV. The Bartik IV interacts the 2008–2012 share of each origin bank's leavers going to PC with the DFAST stress-test distance to regulatory capital floors (binary 1.0 pp indicator for cols (3)–(4); continuous truncated 1.0 pp variant for cols (5)–(6)). Odd-numbered columns include event-year FE only; even-numbered columns add `exp_at_t0`, the worker's cumulative experience at the move.

Table B5: Presence of functions and experience across banks and non-banks - firm level

Panel A: Function Shares

	Sourcing		Diligence		Risk/Approval	
Non-bank	-0.089***	-0.094***	0.044***	0.105***	-0.126***	-0.056***
	(0.012)	(0.020)	(0.011)	(0.017)	(0.011)	(0.018)
Year FE	✓	✓	✓	✓	✓	✓
Controls		✓		✓		✓
Observations	17271	17271	17271	17271	17271	17271
R squared	0.018	0.022	0.006	0.017	0.043	0.058
Mean dep. var.	0.581	0.581	0.632	0.632	0.329	0.329

Panel B: Experience per Classified Employee

	Sourcing		Diligence		Risk/Approval	
Non-bank	-0.812***	-1.133***	0.307*	0.352	-1.146***	-0.691***
	(0.165)	(0.266)	(0.167)	(0.266)	(0.121)	(0.208)
Year FE	✓	✓	✓	✓	✓	✓
Controls		✓		✓		✓
Observations	17271	17271	17271	17271	17271	17271
R squared	0.058	0.075	0.049	0.064	0.062	0.069
Mean dep. var.	4.651	4.651	4.815	4.815	2.417	2.417

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 B6: Robustness of Function Specialization to Classification Coverage

Panel A: Function Shares

	(1) Baseline	(2) % Classified $\geq$ 25%	(3) Classified Emp > 5	(4) Classified Emp > 10
Dep. var.: Sourcing share				
Non-bank (PC)	-0.089***	-0.115***	-0.084***	-0.062***
	(0.019)	(0.023)	(0.018)	(0.019)
Dep. var.: Diligence share				
Non-bank (PC)	0.105***	0.104***	0.062***	0.039**
	(0.016)	(0.021)	(0.015)	(0.017)
Dep. var.: Risk/Approval share				
Non-bank (PC)	-0.054***	-0.059***	-0.080***	-0.076***
	(0.017)	(0.021)	(0.014)	(0.016)
Year FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	9,934	5,467	6,462	5,410
R squared	0.031	0.045	0.043	0.029

Panel B: Experience per Classified Employee

	(1) Baseline	(2) % Classified $\geq$ 25%	(3) Classified Emp > 5	(4) Classified Emp > 10
Dep. var.: Sourcing experience				
Non-bank (PC)	-0.797***	-0.600**	-0.930***	-0.801***
	(0.246)	(0.271)	(0.210)	(0.199)
Dep. var.: Diligence experience				
Non-bank (PC)	0.335	0.804***	0.268	0.222
	(0.259)	(0.278)	(0.211)	(0.235)
Dep. var.: Risk/Approval experience				
Non-bank (PC)	-0.713***	-0.274	-0.783***	-0.596***
	(0.192)	(0.238)	(0.138)	(0.148)
Year FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	9,934	5,467	6,462	5,410
R squared	0.099	0.094	0.246	0.274

Standard errors in parentheses, clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1

Notes: This table tests the robustness of the main specialization results (Table 6) to sample restrictions on classification coverage. Column (1) reproduces the baseline with-controls specification. Column (2) restricts to firm-years where at least 25% of employees have a classified lending function. Columns (3) and (4) restrict to firm-years with more than 5 or 10 classified employees, respectively. Panel A: The dependent variable is the share of classified employees in each function. Panel B: The dependent variable is the total years of functional experience divided by the number of classified employees. Controls include PE fund size share, log firm age, and log number of classified employees. Sample restricted to banks and PC firms, 2013–2023.