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Bankers' Outside Options and Financial Risk

Valentin Kecht[1]
Georg Schneider[2]

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[1]University of Bonn. Email: kecht@uni-bonn.de
[2]University of Bonn. Email: georg.schneider@uni-bonn.de

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Valentin Kecht[†] Georg Schneider[‡]

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Abstract

Firms can discipline workers through the threat of termination, but the value of continued employment depends on job opportunities in the external labor market. We study how bankers' outside options affect risky lending. Using granular employment histories and predetermined coworker links, we construct a time-varying bank-level measure of outside options from hiring at connected financial institutions. A standard-deviation improvement in outside options raises non-investment-grade lending growth by 1.6 to 3.0 percentage points and shifts loans toward borrowers with greater ex-ante and realized risk without detectable compensating loan spreads. Measures of bank and systemic risk also increase. Among individually matched bankers, outside options increase borrower risk and weaken the separation penalty following poor loan performance. The risk response is concentrated among younger bankers, who are more mobile. Financial advisors exhibit a similar pattern of increased misconduct followed by weaker employment penalties under improved outside options. The evidence indicates that workplace discipline is dependent on external labor market conditions, transmitting labor market fluctuations into credit risk.

Keywords: Financial Stability, Risk, Labor Markets, Outside Options
JEL codes: G21, G24, J62, D82, G01

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[†]University of Bonn. kecht@uni-bonn.de

[‡]University of Bonn. georg.schneider@uni-bonn.de

1 Introduction

Firms can discipline workers in different ways, including through the threat of termination. When workers take actions that are difficult to monitor and outcomes arrive with delay, dismissal after adverse outcomes can deter choices that benefit employees at the firm's expense. We argue that the effectiveness of this threat depends on the state of the external labor market. Attractive outside opportunities reduce the cost of job loss and may therefore weaken discipline within the firm. As outside options vary over time, so does the severity of agency problems. Existing research shows that outside options raise pay and mobility (Caldwell and Harmon, 2019; Caldwell and Danieli, 2024; Johnson et al., 2025), while evidence on how they affect workers' actions within their current firms remains limited. We ask whether outside options also affect high-stakes decisions inside firms with ramifications for firm and sectoral performance.

The financial industry is an ideal setting to study this question. Corporate bankers use sector- and borrower-specific expertise to make lending decisions whose performance is revealed with delay, limiting their employers' ability to monitor these choices (Bushman et al., 2021a; Herpfer, 2021; Carvalho et al., 2023). Job-to-job transitions account for a relatively high share of hiring in the financial sector (Azzopardi et al., 2020), making external opportunities relevant to bankers within their current employment spells. The syndicated corporate loans that these bankers arrange are large and the associated credit risk propagates through the syndication process and via secondary markets. Risky credit growth also predicts the likelihood and severity of financial crises (Schularick and Taylor, 2012; Jordà et al., 2013). This setting allows us to follow the consequences of external hiring conditions for high-stakes choices, from individual loans to credit growth and measures of bank and financial-sector tail risk at the lender level.

We present evidence that improved outside options predict riskier conduct and weaken the career consequences associated with adverse outcomes. Banks exposed to better outside options expand lending volumes in the non-investment-grade segment. Outside options also predict faster growth in bank and in financial-sector tail risk. Individual loans shift toward borrowers with greater ex-ante and realized risk, while loan spreads remain unchanged. Among individually matched bankers, outside options reduce the separation penalty following poor loan performance and the risk response is concentrated among younger workers with greater baseline mobility. A complementary analysis of financial advisors yields a similar pattern of more misconduct and weaker subsequent employment penalties. Taken together, these findings support a channel through which better external opportunities reduce the deterrent value of continued employment and make risky choices more attractive.

To formalize this mechanism and guide our empirical analysis, we present a conceptual framework featuring optimal disciplining by banks in the presence of outside options. A banker chooses their screening intensity, trading off the private gains from laxer screening against the increased dismissal risk arising from loan defaults. The employing bank, in turn, sets the dismissal rate applied after a default, weighing lower default losses against the replacement costs of dismissing bankers. When bankers are more likely to receive attractive offers, the dismissal threat is diluted and risk-taking increases. This response is strongest for young bankers, for whom outside offers are more likely to dominate their current match. Since the marginal gain from enforcing discipline is reduced by outside options, banks respond optimally by lowering dismissal rates, further amplifying the effect. Outside offers thus undercut the effectiveness of dismissal, a mechanism we term the discipline dilution channel.

The empirical challenge is to measure outside options without using a given bank's own contemporaneous job mobility patterns or financial performance, as these factors are plausibly correlated with lending behavior. We construct *inflows at ties*, a network-based measure built from employment biographies of senior U.S. bankers. For each bank and quarter, it combines job-to-job hiring at other financial institutions with predetermined coworker links to those institutions, while excluding contemporaneous transitions from the given bank by construction. The measure therefore captures exposure to hiring news from attainable employers using information generated outside the bank in question. This yields a shift-share measure with predetermined exposure shares and exogenous shifts in hiring at other institutions. The measure passes several relevance and design checks. Stronger inflows at ties predict job-to-job mobility and higher salary growth, while transitions out of the financial industry, bonuses and equity at risk show little response. Past outflows and observed bank fundamentals do not predict subsequent inflows at ties. The identifying events are dispersed across roughly 164,000 movers and 367 connected hiring institutions with little common variation over time or within industries and metropolitan areas. The causal interpretation of our results requires a conditional independence assumption, which we examine through a series of diagnostic tests and robustness checks.

We first study outcomes at the level of the lending bank. Better outside options increase lending growth, with a significant increase in non-investment-grade credit. A standard-deviation increase raises non-investment-grade volume growth by 1.6 to 3.0 percentage points across the reported specifications, representing an increase of 2.1 to 4.0% of a standard deviation. Measures of the lending bank's tail risk (VaR) and the financial sector's risk conditional on that bank being in distress (CoVaR) both increase, with effects concentrated in the tail of the risk distribution. In the preferred specification, the 99th percentile VaR and CoVaR responses each equal about 4% of the standard deviation of quarterly risk growth. The parallel VaR and CoVaR responses demonstrate that the increases in lending risk following outside options shocks are detectable in standard measures of bank and systemic risk. The volume and risk results are robust to a series of controls, alternative measures and sample restrictions. Cumulative changes in all three outcomes are positive and statistically significant in the first quarter after a shock and remain positive, though less precisely estimated, at longer horizons.

We then investigate the loan choices underlying the bank-level outcomes. A standard-deviation improvement in outside options raises the probability of lending to a borrower below investment grade by between 0.5 and 1.3 percentage points across fixed-effects specifications. The shift also appears in an alternative ex-ante ratings measure and in borrower book leverage at origination. We find no evidence that banks receive a compensating increase in spreads. Borrowers subsequently experience more severe rating downgrades and pay more when refinancing their next loans. The loan-level response is also attenuated following increases in the enforceability of non-compete agreements at the state level. The findings at the loan level are robust to an extensive set of alternative measures and controls. The two most important sets of checks directly address the concern of correlated lending cycles at connected institutions. First, the estimates remain stable when we control for total and leveraged lending at connected banks and when we add hiring at banks connected through prior co-syndication. Second, the estimates are also robust to segment-time controls that absorb common dynamics across the industries in which connected banks operate.[1]

To empirically test the mechanism we propose, we turn to a subsample of loans for which we observe the identities of individual bankers responsible for arranging each loan. To this end, we extract signatures from SEC loan contracts and match the signers to their employment histories. We report three findings. First, outside options drive ex-post borrower deterioration in this subsample, replicating the loan-level result. Second, although borrower deteriorations raise subsequent separation rates for arranging bankers when outside options are limited, a standard-deviation improvement in outside options offsets 80 to 86% of the estimated separation penalties. Third, we show that realized borrower deterioration is concentrated among younger bankers, who are also significantly more mobile. These findings suggest that outside options influence those bankers who are more likely to move employers, by reducing the penalty associated with adverse lending outcomes and therefore diluting the disciplining effect of dismissal.

Finally, we provide complementary evidence from financial advisors by leveraging annual records from 140,000 individual career histories. Better outside options predict more misconduct disclosures, customer complaints and settled complaints. Outside options also reduce the likelihood of job separation and industry exit after misconduct and raise the odds of reemployment within the financial sector conditional on a misconduct-related separation. In the specification with firm-advisor and firm-year fixed effects, a standard-deviation increase in lagged outside options offsets 19% of the separation penalty, 48% of the conditional industry-exit penalty and 57% of the conditional reemployment penalty. This evidence shows that the mechanism operates in a similar fashion within a distinct but related labor market. Better outside options induce choices that are misaligned with the firm and reduce the effective career penalty from dismissal, leading firms to rely less on this disciplining device.

Our results also speak to the cyclicality of credit supply. Figure 1 shows descriptively that greater labor turnover in the financial industry is associated with looser lending standards. Our evidence supplies a worker-level mechanism running from labor mobil-

[1] We add fixed effects for the lender's dominant connected-bank industry segment interacted with the year, at the two- and three-digit NAICS levels. We also add a control for weighted hiring in connected banks' industry segments.

Figure 1: Financial Sector Labor Market Turnover and Lending Standards

Notes: The figure bins voluntary labor market turnover in the financial sector against changes in lending standards. Labor market turnover is the sum of hiring and quit rates in financial activities (FRED series JTU510099HIL and JTU510099QUR), transformed into first differences. Lending standards are measured by the net percentage of domestic banks tightening their standards across loan categories. We use the SLOOS net percentage of domestic banks tightening standards across loan categories, weighted by banks' outstanding loan balances by category, from FRED series SUBLPDMOSXWBNQ.

ity to lending decisions within incumbent banks. When cross-firm hiring strengthens, improved outside options weaken dismissal-based discipline and shift lending toward greater volume and risk. Because outside options tend to improve during expansions (Mortensen and Pissarides, 1999; Nakamura et al., 2019; Figueiredo, 2022), this mechanism can make agency problems and lending risk procyclical. As credit growth predicts the likelihood and severity of financial crises (Schularick and Taylor, 2012; Jordà et al., 2013), this channel links labor market conditions to financial stability.

These findings also have implications for financial supervision. Supervisors could encourage compensation structures that promote retention over longer horizons. Regulators could also publish standardized data on hiring and mobility in systemically important parts of the financial sector, allowing firms and supervisors to identify periods in which unusually strong outside opportunities may weaken internal discipline.

Literature. Our first contribution is to the literature on outside options and workplace discipline. Existing work shows that outside options shape worker pay and mobility (Caldwell and Harmon, 2019; Caldwell and Danieli, 2024; Caldwell et al., 2024; Schubert et al., 2022; Jäger et al., 2024) and may affect effort (Ahammer et al., 2023). A separate literature reaches differing conclusions about whether adverse outcomes damage financial professionals' careers. Corporate credit events increase banker turnover and change subsequent lending behavior, while bankers associated with mortgage securities face little career penalty following the great financial crisis (Gao et al., 2020; Griffin et al., 2019; Hamdi et al., 2023; Ellul et al., 2020). We show that reemployment prospects help explain when career discipline operates effectively. Poor performance carries a smaller separation penalty when outside opportunities are better, with workers responding by taking greater risks. Our evidence from corporate bankers and financial advisors shows that external labor demand affects behavior at the employing firm before mobility occurs. This finding also identifies labor market conditions as another determinant of banker lending choices documented in syndicated lending (Herpfer, 2021; Bushman et al., 2021b; Carvalho et al., 2023).

Our second contribution is to show how this organizational mechanism links labor markets in the financial sector to financial risk. Theory establishes that banker career rents and competition for talent can amplify moral hazard and credit cycles (Myerson, 2012, 2014; Thanassoulis, 2012; Axelson and Bond, 2015; Acharya et al., 2016; Boxtel, 2017). Empirical work shows that realized mobility and legal restrictions affect screening and capital allocation (Gao et al., 2024a,b; Cici et al., 2021; Agarwal et al., 2024; Bonelli, 2019; Norden et al., 2025). We identify an anticipatory channel operating within an ongoing employment relationship: labor demand at potential employers weakens the dismissal threat and shifts lending toward greater volume and risk. These changes also appear in bank and financial-sector tail risk. Our findings thus locate part of the risk buildup that precedes financial crises (Schularick and Taylor, 2012; Jordà et al., 2013) in labor market dynamics in the financial sector.

The remainder of the paper proceeds as follows. Section 2 develops the conceptual framework and its predictions. Section 3 describes the linked data and Section 4 constructs the outside options measure and states the identifying assumptions. Section 5 presents lender-level volume and risk results before turning to loan-level borrower outcomes. Section 6 uses individually matched corporate bankers to study age heterogeneity and the dilution of discipline, then presents complementary evidence from financial advisors. Section 7 concludes.

2 Conceptual Framework

To interpret our results, we lay out a framework capturing how banks govern banker risk-taking under moral hazard. In the presence of information frictions, a bank disciplines a banker by imposing a penalty after adverse outcomes, but better outside options erode the effect of that penalty. We focus on the penalty of discontinued employment, as bankers who perform poorly can be dismissed and lose the value of the ongoing relationship. An accepted outside offer protects the banker by allowing them to depart before the loan outcome is observed.

Two features affect how this discipline dilution channel operates. First, firing is costly to the bank, so the intensity of the dismissal threat is an equilibrium object. We show that banks optimally reduce discipline as offers become more likely, even though they correctly anticipate the resulting increase in risk-taking. Second, an outside offer affects discipline only when the banker is able and willing to exercise it through departure. We embed the lending game in a minimal on-the-job search environment in the spirit of Burdett and Mortensen (1998). Over a career, a banker samples offers and moves only to better matches. An offer is attractive only if it is better than any previous draw, an event whose probability declines mechanically over time. Because outside options are more likely to be attractive for young bankers than for older bankers, fluctuations in labor demand at other banks dilute discipline more for the former group.

Setup. There are three dates, $t = 0, 1, 2$ and two risk-neutral players, a bank and a banker. The banker has no wealth and is protected by limited liability. The disciplinary instrument at the bank's disposal is the dismissal threat. The bank commits at $t = 0$ to a dismissal probability $\delta \in [0, 1]$ applied to a banker who holds no actionable outside offer and whose loan defaults at $t = 2$. A dismissed banker forfeits the value $D \geq 0$ of continued employment, which includes any unvested deferred pay (Edmans et al., 2017; Hoffmann et al., 2022).

We assume that the bank has chosen an approval cutoff $\bar{z}$ for increasing borrower quality z under prevailing borrower fundamentals and bank balance-sheet conditions. We take this target as given throughout the model. The banker chooses unobserved screening laxity $r \in [0, a]$ and implements the cutoff $z^*(r) = \bar{z} - r$, where a is the largest feasible relaxation. Thus, $r = 0$ implements the bank's target, while higher r allows additional borrowers below that target to obtain a loan. Assuming a uniform density of applicants over the relevant range and normalizing it to one, the mass of additional risky approvals equals r. Because laxity is unobserved, the firing decision can only be conditioned on the default outcome (Holmström, 1979). We also assume non-observability of defaults across banks.

Laxity yields the banker a private benefit $g(r) = ar - r^2/2$, which is increasing and concave on $[0, a]$. It captures, in reduced form, saved effort of screening borrower firms, performance bonuses for arranging additional loans and career benefits from being associated with successful deal arrangements. This is consistent with the tension between originating more loans and screening borrowers more thoroughly, studied in the literature on loan officers (Heider and Inderst, 2012; Behr et al., 2020). Relative to the bank's target, the additional risky approvals raise the default probability by $p(r) = \gamma r$, with $\gamma > 0$ and $\gamma a \leq 1$ and impose the expected excess default loss $\ell(r) = hr$ on the bank.

We model the dismissal costs for the bank as increasing and convex in dismissal strictness,

$$C(\delta) = \frac{k}{2}\delta^2, \qquad k > 0. \tag{1}$$

A stricter dismissal policy creates more vacancies at the bank level, which become increasingly difficult to fill with qualified candidates because banks hire few experienced workers from outside the financial sector.

Career age. Before the lending game, the banker has spent a career in the sector, which we summarize by the number $n \geq 1$ of match values the banker has sampled, drawn i.i.d. from a continuous distribution F. This count grows with time in the labor market and can be interpreted as career age. Because a searching worker moves only to matches better than the current one, the banker enters the lending game occupying the best match sampled so far,

$$v_n = \max\{x_1, \ldots, x_n\}. \tag{2}$$

This is the core selection mechanism in on-the-job search models (Burdett and Mortensen, 1998; Jovanovic, 1979), in which seniority and match quality accumulate together.

At $t = 1$, before loan outcomes are observed, the banker receives an offer $x \sim F$ with probability λ. Denote the new total number of draws by $\eta \equiv n+1$. The offer is an attractive option only if it dominates the incumbent match, $x \geq v_n$. The probability of this event does not depend on F and is given by $1/\eta$. The arrival rate of dominating offers is

$$\lambda_d(n) = \frac{\lambda}{\eta}. \tag{3}$$

Conditional on receiving a dominating offer, the incumbent firm chooses not to match the offer with probability $\mu \in (0,1)$, in which case the banker departs. Otherwise, the banker accepts a matched contract from the incumbent. The rate of job-to-job departures equals the effective insurance rate and amounts to

$$\lambda_I(n) = \frac{\lambda\mu}{\eta}.$$

That is, protection against downside risk arises only when a dominating offer arrives and is not matched by the incumbent firm, because departure places the banker beyond the incumbent bank's reach before dismissal at $t = 2$. A banker who accepts the incumbent's matched contract receives the higher bargained pay associated with a credible outside offer but remains subject to dismissal if the loan subsequently defaults.[2] Once the banker accepts or declines an offer, the offer expires. A dominated offer is declined without affecting either bargaining or dismissal exposure.

The banker's choice. The banker retains employment value D unless the banker remains with the incumbent, the loan defaults and dismissal occurs. Expected utility is

[2]In a matched state, the incumbent and the banker divide the surplus of the continued match V by Nash bargaining. Given a dominating offer x and banker bargaining weight $\beta \in [0,1]$, the retained wage solves $\max_{w_m}(w_m - x)^\beta (V - w_m)^{1-\beta}$, giving $w_m = \beta V + (1-\beta)x$. The banker occupies a matched state with probability $\lambda(1-\mu)/\eta$ and is otherwise paid a base wage $w_0 = \beta V + (1-\beta)v_0$, with v_0 the banker's outside value absent an offer, so $w_0 < w_m$. Hence, both expected pay and departures increase with outside options.

$$U(r) = w + g(r) + \left[1 - \left(1 - \frac{\lambda\mu}{\eta}\right) p(r)\,\delta\right] D, \tag{4}$$

where w is the banker's expected bargained pay. The first-order condition

$$g'(r) = \left(1 - \frac{\lambda\mu}{\eta}\right) p'(r)\delta D$$

yields

$$r^* = a - \gamma\left(1 - \frac{\lambda\mu}{\eta}\right)\delta\, D. \tag{5}$$

That is, holding the dismissal rate constant, risk-taking increases with the arrival rate of outside offers.

The bank's problem. With additive base pay dropping out, the bank chooses the firing intensity by solving

$$\max_{0\le\delta\le1} \; -h\,r \;-\; \frac{k}{2}\,\delta^2, \qquad r = a - \gamma\left(1 - \frac{\lambda\mu}{\eta}\right) D\,\delta. \tag{6}$$

Writing $B(n) \equiv \gamma\left(1 - \frac{\lambda\mu}{\eta}\right) D$ for the marginal disciplinary power of the firing threat, risk-taking follows $r = a - B\delta$. With a linear excess default loss function, the first-order condition $hB = k\delta$ yields

$$\delta^*(n) = \frac{hB(n)}{k}, \qquad r^*(n) = a - \frac{hB(n)^2}{k}. \tag{7}$$

Discipline is interior, $\delta^* < 1$, whenever $h\gamma D \,<\, k$, a single condition that holds uniformly across career ages since $B(n) \le \gamma D$. That is, we assume that the firing cost is large enough that the bank does not dismiss every uninsured defaulter, consistent with Gao et al. (2020), who find that banks do not dismiss every banker following adverse outcomes.

Comparative statics. The bank's first-order condition equates the marginal value of disciplining the banker to its marginal cost. An increase in λ raises the probability that the banker departs on an unmatched dominating offer before the loan outcome is realized.

This lowers the marginal effect of dismissal intensity on risk-taking, B, and leads the bank to choose a lower δ. Differentiating equilibrium risk in Equation (7),

$$\frac{\partial r^*}{\partial \lambda} = \frac{2h\gamma^2 D^2}{k}\,\frac{\mu(\eta - \mu\lambda)}{\eta^2} \;>\; 0, \tag{8}$$

shows that risk rises with the offer rate even though the bank has chosen firing optimally. The bank cannot eliminate this effect by adjusting dismissal strictness because the source of the distortion lies outside the employment relationship and with the hiring decisions of rival firms. The distortion is thus an externality across employers competing for the same talent, complementing accounts in which competition for bankers shapes pay and risk-taking in equilibrium (Thanassoulis, 2012; Acharya et al., 2016).

The model also speaks to the firing decision itself. Differentiating the chosen intensity in Equation (7),

$$\frac{\partial \delta^*}{\partial \lambda} = -\frac{h\gamma D}{k}\,\frac{\mu}{\eta} \;<\; 0, \tag{9}$$

we see that the bank fires less intensely when λ rises. This qualifies the findings of Gao et al. (2020), since the career penalty itself depends on labor market outside options. The effect is proportional to $1/\eta$, with larger reductions in separation penalties for bankers who are more likely to act on offers.

The accumulation of match draws over a career implies that the risk response to offer arrivals declines with career age. Differentiating the risk response (8),

$$\frac{\partial^2 r^*}{\partial \lambda\,\partial \eta} = -\frac{2h\gamma^2 D^2}{k}\,\frac{\mu(\eta - 2\mu\lambda)}{\eta^3} \;<\; 0 \qquad \text{for all } \eta \geq 2, \tag{10}$$

since $\lambda \leq 1$. The response of risk-taking to improved outside options is more pronounced among young bankers, for whom offers are more likely to be acceptable. The same mechanism governs mobility itself. Departures occur at rate $m(n) = \lambda\mu/\eta$, which declines with career age and rises with outside options. The mobility response to outside options, $\partial m/\partial \lambda = \mu/\eta$, is therefore likewise concentrated among the young.

Predictions. The framework yields three groups of testable predictions.

1. **Pay and mobility.** Improvements in outside options raise both the expected pay of retained bankers and the rate of departures $\lambda\mu/\eta$, as banks match and raise pay for a share of dominating offers and the remaining bankers depart when those offers are not matched. Because the probability that an offer dominates falls with career age, mobility and its response to outside options are concentrated among young bankers.

2. **Risk taking and misconduct.** As better outside options dilute the threat of dismissal, bankers relax the implemented approval cutoff. More risky borrowers clear screening, increasing the volume of risky credit. This result operates through actionable outside offers and is weaker if labor mobility is restricted. With better outside options, the bank also reduces firing conditional on bad realizations. The same mechanism predicts more misconduct by financial advisors, who receive immediate private gain from advice of lower quality and delayed revelation of outcomes to clients.

3. **Heterogeneity.** The risk response to outside options declines with banker age. Among young bankers, offers are more likely to dominate their current match and provide effective insurance, making them more responsive to fluctuations.

Discussion. Three implicit assumptions deserve comment. First, changes in other banks' hiring behavior move bankers' outside options, which is reasonable given limited entry into the sector and the prevalence of job-to-job transitions (Philippon and Reshef, 2012; Bell and Van Reenen, 2014; Böhm et al., 2023). Second, individual bankers influence loan decisions, for which there is extensive evidence in the syndicated loan market (Herpfer, 2021; Bushman et al., 2021b; Carvalho et al., 2023) and more broadly that loan officers' incentives shape credit provision (Hertzberg et al., 2010). Third, we model the banker as risk-neutral to isolate the contractual channel. A risk-averse banker would view dominating offers as insurance against the income loss following dismissal, reinforcing the prediction.

Behavioral channels could operate alongside the contractual one we highlight. Favorable labor market news could make bankers optimistic about their own portfolios and lead to riskier lending (Bordalo et al., 2024). The individual-level results on bankers and financial advisors are, however, difficult to reconcile with optimism alone, as they show that the labor market penalties for lax screening and misconduct fall when outside options improve. Similarly, bankers may use a stronger labor market position to bargain for more generous severance or greater lending discretion. Both are possible mechanisms within the broader channel in which outside options weaken employer control, so our framework abstracts from such bargaining for parsimony.

3 Data

We construct a linked dataset that connects labor-market conditions to bank-level outcomes, individual loans and banker careers. We focus on the syndicated lending market for three main reasons. First, both the size of individual loans and the size of the overall loan market make syndicated loans important for financial stability. With a median loan size in our sample of USD 400 million, these contracts represent high-stakes decisions. In 2018, the USD 2.8 trillion syndicated lending market exceeded the USD 1.3 trillion corporate bond market (SIFMA, 2019). Second, default risk can spread through syndication, secondary-market trading and securitization (Mugasha, 2004). Finally, lending choices can be attributed to arranging banks and, for the matched subsample, to individual signers. Prior work shows that these lead bankers can influence loan design (Herpfer, 2021; Bushman et al., 2021b).

Dealscan. We obtain data on bank lending activity from *Dealscan*. From the universe of loans recorded in the database, we identify the 1,500 largest lead-arranging banks by number of loans issued and include all tranches arranged by these banks in our sample. For each loan, we include the identities of the borrowing and lending firms, the tranche amount and maturity, as well as indicators for whether the loan is secured and whether covenants are attached. Table A1 reports summary statistics for the tranche-level data. To measure credit quantity, we also aggregate the data to the lender-quarter level to obtain the number of loans and total lending volume.

Revelio Labs. We draw on labor market data from Revelio Labs, which collects employment biographies reported on LinkedIn. The dataset includes employment details for the universe of public profiles, covering nearly 500 million workers across approximately 1.8 billion employment spells. The linked employer-employee data contain employment spell start and end dates, as well as self-reported job titles. From this information, Revelio Labs generates a task-based classification of job titles, which maps activities to each title by analyzing descriptions from resumes and online profiles, alongside responsibilities listed in job postings.[3] Initially, the algorithm identifies 1,500 job roles, which are successively aggregated using a clustering algorithm. The data also include a seniority ranking derived from job titles, ranging from 1 (lowest) to 7 (highest).

To construct our sample of senior bankers, we proceed as follows. First, we exclude all employment spells outside the United States. Second, we use the job taxonomy at the hierarchical level that defines 300 distinct roles, allowing us to identify the individuals employed in the relevant roles.[4] Third, to identify senior bankers, we retain spells with a seniority level of 4 or above. Finally, we retain full-time bankers by excluding overlapping spells. We use all employment spells between 1994 and 2020.[5]

Panel A of Table A2 reports summary statistics for this sample. The sample predominantly consists of male, white and highly educated employees with average annual incomes of around USD 150,000. Because the employment histories are backfilled, the mean employee age is relatively young at 37 years. Table A3 compares key demographic variables between the LinkedIn dataset and widely used survey data sources. The sample captures the main characteristics of individuals employed in the financial industry reported in the CPS and ACS.[6] These similarities are stronger when we remove the seniority restriction.

For our main analysis, we combine the Dealscan lending data with an outside options proxy calculated from employment histories at the parent-company level. We sequentially merge on exact matches of parent companies' GVKEYs, tickers and company

[3]For additional details, see www.reveliolabs.com.

[4]The included roles are "Investment Specialist", "Investment Banking", "Banker", "Credit Specialist", "Financial Advisor", "Loan Officer" and "Financial Analyst". The broad set of roles is motivated by the fact that the role taxonomy in our data remains coarse within finance, as we verified manually in the sample of individual loan signers. The wider scope also reflects potential moves into related financial markets that constitute outside options. Using the same set of roles for the banker and advisor analyses further ensures consistency across the two analyses.

[5]The data have been collected since 2019 but contain all self-reported employment spells from earlier periods.

[6]We obtain both sources through IPUMS. For details on the ACS data, see Ruggles et al. (2025).

names, which we clean and normalize beforehand, retaining only unique matches. For unmatched observations, we repeat the procedure at the subsidiary level, linking parent companies through their subsidiaries when matches are identified. When multiple subsidiaries match, we prioritize the match associated with the highest number of spells for each lender parent. We manually verify all matches and identify additional ones. In this way, we merge 1,268 parent companies, comprising two-thirds of the subsidiaries in Dealscan. Among the 1,000 largest lenders, the matched sample accounts for 99% of individual loans and 91% of total lending volume.

For a limited sample of loans, we identify individual lead-arranging bankers by name and affiliation and match them to their respective employment histories. Following Herpfer (2021), we obtain syndicated loan contracts from SEC filings and parse their signature blocks to recover each signer's name, title and lender affiliation. We link the contracts to Dealscan loans by borrower and origination date within a 91-day window, retaining the lender identity recorded in the signature block. We then match signers to their employment histories by name and lender affiliation and require the corresponding employment spell to overlap the contract date, allowing 31 days around reported spell boundaries. This procedure yields 2,398 signer-loan observations covering 1,243 bankers and 66 lenders before loan outcomes are attached. Panel B of Table A2 reports summary statistics for this sample.

Compustat. We obtain data on firm-level fundamentals from Compustat. For both borrowing and lending firms, we include ratings, assets, liabilities, net income, EBIT, short-term debt, long-term debt, employees, shareholders' equity and capital expenditure. We also use borrowers' S&P credit ratings as a measure of credit risk and repayment probability. We use the linking tables of Chava and Roberts (2008) and Schwert (2020) to match borrower and lender firms in Dealscan and Compustat. Panels A and B of Table A4 report the summary statistics.

Mergent FISD. We use Mergent's Fixed Income Securities Database (FISD) to obtain bond credit ratings, rating actions and defaults from Moody's, S&P and Fitch. For each loan tranche, we construct a contemporaneous issuer rating as the median of the most recent active ratings, on or before origination, across the borrower's bonds and rating agencies. We map ratings to a 22-point scale ranging from 1 (D) to 22 (AAA/Aaa). Table A1 reports summary statistics for the rated-loan subsample.

(Conditional) Value at Risk. To measure financial risk, we use the quarterly data of Adrian and Brunnermeier (2016), which span 1994 to 2009. The first measure is Value at Risk (VaR), which captures the maximum loss for institution i at the 95% or 99% confidence level and thus the financial risk of the lending bank. The second variable is Conditional Value at Risk (CoVaR), defined as the VaR of the financial sector conditional on bank i being in distress. CoVaR quantifies the expected loss to the financial system conditional on a 95th- or 99th-percentile loss at bank i, capturing the noncausal contribution of bank i to systemic risk. Adrian and Brunnermeier (2016) estimate these measures using quantile regressions. We transform the data into symmetric growth rates and report summary statistics in Table A4.

BoardEx. We use information on banker pay from BoardEx, a database provided by *Delinian*. These data include detailed information on compensation for top executives of large, listed companies in the United States since 1997. Summary statistics are reported in Appendix Table A5. We construct year-over-year growth rates in the firm-level median of salaries, bonuses and equity at risk. To better capture wage bargaining, we restrict the sample to roles with operational responsibilities rather than a board-level oversight and governance role.[7] Summary statistics are shown in Panel D of Table A3.

Investment advisor data. We use data on misconduct among U.S. investment advisors, covering individuals registered with the Securities and Exchange Commission (SEC), a state authority or both. The dataset is a panel spanning 2007 to 2015 and includes detailed employment histories alongside annual counts of misconduct disclosures and customer complaints. We combine this information with our measure of outside options at

[7]This includes all role names containing “Director”, “President”, “VP”, or “MD”, excluding those that contain “CEO”, “Chair”, “Trustee”, or “Partner”.

the parent-company level, matching sequentially on CIK, web domain and bank name. The final sample includes approximately 140,000 distinct individuals.[8]

4 Measuring Outside Options

This section describes our measure of outside options, followed by validation tests and a discussion of the identifying assumptions. The measure generates differential exposure to hiring at other banks using predetermined coworker connections to those institutions and is constructed independently of each bank's own contemporaneous employment dynamics.[9]

Construction. Our outside options measure counts new senior finance hires at other firms, weighted by the share of former coworkers now employed there, capturing bank-time variation in exposure to signals about labor market dynamics at broadly attainable firms. More formally, for bankers at a given bank i in quarter t, our measure of outside options is defined as follows:

$$InflowsAtTies_{it} = \sum_{j \neq i} w_{ijt} \times Inflows_{-i,jt} \tag{11}$$

Thus, $InflowsAtTies_{it}$ is the weighted sum of inflows at other banks j, denoted by $Inflows_{-i,jt}$. The latter term is defined as job-to-job transitions by senior finance workers from all other firms $k \neq i$ to firm j in quarter t:

$$Inflows_{-i,jt} = \sum_{k \neq i} Transitions_{kjt}. \tag{12}$$

[8]Egan, Matvos and Seru construct the underlying data using publicly available records from the SEC's Investment Advisor Public Disclosure website. For additional details, see Egan, Matvos and Seru's homepage, Egan et al. (2019, 2022) and the recent literature review by Egan et al. (2024).

[9]The role of social networks in shaping labor market outcomes has been extensively documented both theoretically (Montgomery, 1991; Dustmann et al., 2016) and empirically (Bramoullé and Saint-Paul, 2010; Shue, 2013; Hensvik and Skans, 2016; Glitz, 2017; Gee et al., 2017; Saygin et al., 2021; Cingano and Rosolia, 2012).

We exclude transitions from firm i to j in t from the hiring component. This mechanically isolates the measure from the contemporaneous outflows of a given bank that might be related to factors also influencing lending decisions.

The weights measure the share of former coworkers now employed at other banks. More specifically, the weight bank i attributes to j at time t counts the number of past transitions from the former to the latter, normalized by the number of past transitions from i to all other banks:

$$w_{ijt} = \frac{\sum_{h=4}^{12} Transitions_{ij,t-h}}{\sum_{m \neq i} \sum_{h=4}^{12} Transitions_{im,t-h}}. \tag{13}$$

The weights thus capture the social ties workers of a given bank have to other firms that expose them to information about hiring at those firms.[10] In our baseline specification, we focus on ties that are between 4 and 12 quarters old. We limit the tie duration to 3 years because social ties weaken over time and the former coworkers might move on to a third firm. Consistent with our choice of the upper bound, we find that the median spell length in our sample is around 13 quarters. We begin including ties only one year after the transition to ensure that outflows from a firm do not mechanically affect the contemporaneous weight component of our measure. A bank's outflows in a given quarter therefore enter neither the hiring nor the weight component of the measure in that quarter. We demonstrate the robustness of our main results to alternative timing assumptions in the appendix.

The measure $InflowsAtTies_{it}$ was initially proposed by Caldwell and Harmon (2019) and has several properties that make it well suited to our setting. First, it captures firm-level variation in signals about labor demand, shifting workers' beliefs about their outside options. Prior work shows that such beliefs affect not only the job search and bargaining intentions of workers (Jäger et al., 2024) but also their search and bargaining outcomes (Caldwell and Harmon, 2019). We expect this information transmission channel to be relevant, given the importance of professional (Godechot, 2014) and alumni networks (McNamara and McLoughlin, 2009) and the widespread use of LinkedIn in the financial

[10] The LinkedIn dataset does not include information about connections between profiles. We are therefore unable to base our network measure on social ties indicated by these connections. Instead, we assume that ties form between senior investment bankers working at the same firm at the same time and persist for a limited period after one banker moves to another firm.

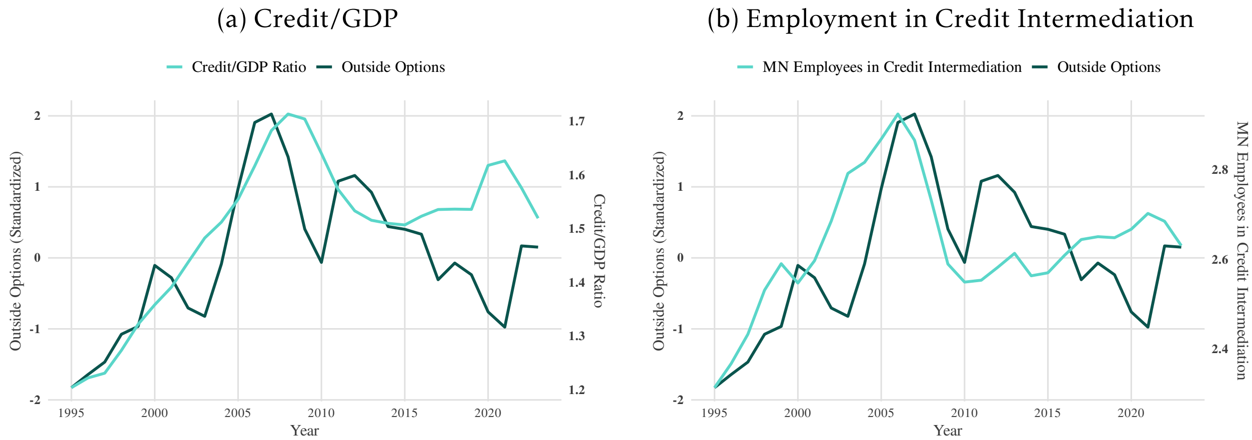
industry (Fracassi et al., 2016; Jiang et al., 2018). In many cases, senior positions remain unadvertised, increasing the reliance of bankers and banks on established network connections and employee referrals. Second, the weighting approach provides an intuitive method of accounting for a bank i's worker placement record in the recent past. Employees should place more weight on labor demand at firms that are achievable for them, which our proxy captures. Because we weight inflows by the share rather than the number of ties, firm size and the corresponding size of the coworker network do not mechanically inflate the proxy. Third, the measure relies exclusively on variation in employment flows across firms. Alternative approaches (such as those in Caldwell et al., 2024) based on worker concentration across industries or occupations are unsuitable in the context of a single occupational group. We also refrain from relying on spatial variation in our setting, given the concentration of senior investment bankers in a small number of financial hubs as well as potential demand-side effects (Ee et al., 2023; Ee and Huang, 2024).

To construct the measure, we identify senior investment bankers as those with at least one employment spell that meets the exclusion criteria outlined in Section 3. Next, we retrieve the employment histories of these individuals to trace their connections to other institutions. We also extract all senior investment banking spells of workers at those other firms. For the hiring dynamics, we focus on job-to-job transitions, which we define as those with employment gaps of one month or less. In a given quarter, we observe on average 317 bankers per institution, with 24 connected banks, each of which hires 7 bankers.[11] Based on this sample of spells, we compute $InflowsAtTies_{it}$ in the way described above and standardize the resulting measure to have a mean of zero and a standard deviation of one. As we plot in Figure 2, the outside options measure follows broader trends in financial activity, moving closely with the credit-to-GDP ratio and the number of employees in credit intermediation.

Validation. We validate the relevance of the measure by replicating the findings of Caldwell and Harmon (2019) on the effects of outside options on mobility and wages. To examine the relationship between outside options and employee mobility, we regress employee outflows from a given institution on our proxy for outside options, including bank and year-quarter fixed effects. We estimate separate models for each lead and lag

[11] See Table A6 for summary statistics.

Figure 2: Evolution of Inflows at Ties over Time



Notes: The plot shows average inflows at ties over time against the credit-to-GDP ratio (Panel (a)) and the number of employees in credit intermediation (Panel (b)). We obtain the aggregate data from FRED, using series QUSPAM770A and CEU5552200001.

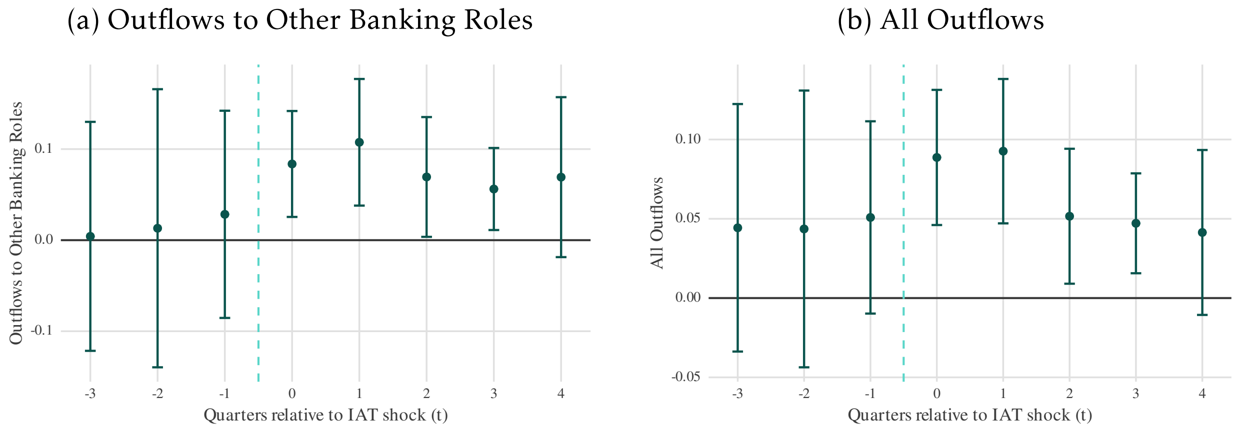
of the outside options measure. Figure 3 reports the results for moves to other banking roles in Panel (a) and for all employee outflows in Panel (b). Outside options significantly increase both measures of outflows on impact and in subsequent periods. This persistence is consistent with news shocks shifting beliefs and influencing search behavior over the short and medium term. The coefficients on the leads are not significant, indicating that elevated past outflows do not predict our outside options proxy. The pattern also remains unchanged for alternative timing assumptions for the construction of $InflowsAtTies_{it}$ (Figure A1).

At the spell level, we similarly find that a shock in outside options increases subsequent worker mobility. Appendix Table A7 shows that a standard-deviation increase in $InflowsAtTies$ raises the probability of a job-to-job move over the next two years, while leaving moves out of finance essentially unchanged.[12]

Second, we examine whether better outside options translate into pay increases for employees who remain with their firms. To this end, we regress midpoint growth rates of firm-level compensation components on our outside options proxy, controlling for lender

[12]Consistent with the age discussion in our framework, mobility is higher among less senior bankers in the same specifications.

Figure 3: Outside Options and Employee Outflows



Notes: Points show coefficients from separate Poisson regressions of employee outflows on inflows at ties at horizons from three quarters before through four quarters after the shock. Panel (a) restricts outflows to roles at other banks in our sample, while Panel (b) includes all destinations. Whiskers show 95% confidence intervals based on two-way clustered standard errors at the lender and year-quarter levels. All regressions include lender and year-quarter fixed effects. Inflows at ties are standardized to have mean zero and standard deviation one.

and year-quarter fixed effects. Table A8 presents the results. Columns (1) and (2) show that improved outside options are associated with substantial increases in median salary growth, with and without lender controls. Columns (3) to (6) consider other key compensation components, bonuses and equity at risk, and find no significant response to variation in outside options. This contrast indicates that, conditional on controls and fixed effects, the proxy does not capture cyclical variation in the financial position of banks, as we would otherwise expect more volatile pay components to respond more strongly. It also aligns with prior evidence that workers primarily bargain over wages rather than bonuses or amenities (Caldwell et al., 2024). Overall, the results indicate that banks raise fixed pay to retain talent when outside options improve, supporting the interpretation that our proxy reflects meaningful variation in outside options.

Identification. Our estimand of interest is the effect of a change in the exposure of a bank to hiring at connected institutions on its lending and risk outcomes. We can give the coefficient a causal interpretation under the assumption that, conditional on controls and fixed effects, the hiring shifts transmitted through the network are unrelated to unobserved determinants of the focal bank's outcomes.

The empirical strategy is a panel shift-share design, with the tie weights w_{ijt} as shares and job-to-job inflows $Inflows_{-i,jt}$ at connected banks as shifts. We follow the exogenous shifts approach of Borusyak et al. (2022, 2025), under which identification comes from conditionally quasi-random hiring shifts that are sufficiently dispersed across connected institutions. The network weights themselves need not be exogenous and may reflect persistent bank characteristics.

Hiring at a connected institution can arise for a number of reasons, including retirements, leadership changes or team-level staffing needs. To support our reliance on such idiosyncratic variation, we present several diagnostics. First, current bank balance-sheet variables, in levels and growth rates, do not predict subsequent inflows at ties after lender and year-quarter fixed effects (Tables A9 and A10). Second, the validation exercise for job mobility also shows no elevated outflow coefficients before the measured outside options shock in either panel of Figure 3. These tests also provide evidence against reverse causality operating through observed bank conditions or prior mobility.

The underlying shocks are widely dispersed. The average bank is connected to 24 institutions in a quarter, while 367 connected banks record positive hiring over the sample. The largest average shock exposure is 2.7%[13] and the average bank is connected to about 7% of the hiring institutions. Year-quarter fixed effects account for about 2% of the variation in hiring behavior. After residualizing for them, correlations within three-digit NAICS industries and metro areas range from 0.02 to 0.04 (Table A11), providing evidence that hiring behavior is dispersed even within narrow sectors and regions. A remaining concern is bank-specific exposure to a common or industry-level shock that affects both hiring at connected banks and the lending at bank i (Guren et al., 2021). We address this concern in Section 5, using several robustness checks. Worker transitions underlying these shocks are likewise dispersed. Serial switching is rare, with the large majority of movers transitioning only once over the entire sample period and four or more moves being exceptional (Figure A2). The inflow events are also broadly dis-

[13]Randomly sampling a bank-quarter and then sampling a connected bank according to the tie weights in that quarter yields the most connected bank in 2.7% of cases.

persed across movers, as the most frequently mobile 1% account for only about 4% of all transitions and the Gini coefficient of events across movers is just 0.18 (Figure A3).

5 Main Results

This section presents the main results. We begin with the effects of outside options on outcomes at the lender level and study the timing of these responses. We then turn to loan-level choices and test whether the composition and subsequent performance of borrowers move in the direction implied by our conceptual framework.

5.1 Lender-level Outcomes

We ask whether improved outside options drive risky credit expansion and faster growth in bank and systemic risk. As discussed in Section 2, the framework predicts both to increase, as more potential borrowers pass a lowered screening threshold when the dismissal threat weakens. To test this, we estimate the following specification for bank i in year-quarter t:

$$y_{it} = \beta InflowsAtTies_{it} + \alpha_{i,yr} + \lambda_t + \epsilon_{it} \tag{14}$$

where y_{it} is the outcome of interest, measured quarterly. The terms $\alpha_{i,yr}$ and λ_t are fixed effects at the bank-year and year-quarter level. Standard errors are two-way clustered at the lender and year-quarter level.

Loan Volume. We assess the effects of outside options on lending volumes constructed from the syndicated loan data, with results presented in Table 1. We measure a bank's quarterly lending volume as the total amount of the facilities in which it is a lead arranger.[14] The dependent variable is the midpoint growth rate of this volume in percentage points. We report total lending in Columns (1) and (2), its non-investment-grade component in Columns (3) and (4) and its investment-grade component in Columns (5) and (6). Within each block, the first specification includes bank and year-quarter fixed effects,

[14]We credit each lead arranger with the full amount of a facility exactly once to correct for facilities that recur across a parent's subsidiaries and loan amendments.

Table 1: Effect of Outside Options on Loan Volume

	Total		Non-Inv. Grade		Inv. Grade	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Baseline						
IAT	0.395	0.221	1.551***	3.047***	0.344	0.649
	(0.690)	(1.561)	(0.387)	(1.006)	(0.736)	(1.556)
Panel B. Controlling for In- and Outflows						
IAT	0.393	0.277	1.584***	3.041***	0.362	0.753
	(0.696)	(1.551)	(0.395)	(0.986)	(0.744)	(1.532)
Inflows to i	X	X	X	X	X	X
Outflows from i	X	X	X	X	X	X
Panel C. Controlling for Lending at Ties						
IAT	0.823	0.647	1.757***	3.472***	0.780	0.927
	(0.805)	(1.600)	(0.480)	(1.057)	(0.828)	(1.604)
Lending at ties, level	X	X	X	X	X	X
Lending at ties, growth	X	X	X	X	X	X
Panel D. Controlling for Inflows at Borrowers (IAB)						
IAT	0.392	0.215	1.550***	3.050***	0.340	0.642
	(0.690)	(1.562)	(0.387)	(1.006)	(0.736)	(1.557)
IAB	X	X	X	X	X	X
Lender FE	X		X		X	
Lender × Year FE		X		X		X
Year-Quarter FE	X	X	X	X	X	X
Observations	25,378	25,219	25,378	25,219	25,378	25,219

Notes: Panel A reports the baseline estimates. Panel B controls jointly for lender i inflows and outflows. Panel C jointly controls for exposure-weighted levels and annual growth rates of four lending measures at connected banks. These measures cover total syndicated lending and leveraged lending defined using spreads of at least 200 basis points, borrowers rated below investment grade or loan purposes associated with buyouts, mergers and acquisitions and recapitalizations. Panel D controls for standardized inflows at borrowers, *IAB*, measured as the senior financial worker inflows at firms with an active borrowing relationship with lender i. The dependent variable is the midpoint growth rate, transformed into percentage points, for a bank's quarterly lead-arranged lending volume. Columns (1)–(2) use total lending volume, Columns (3)–(4) its non-investment-grade component and Columns (5)–(6) its investment-grade component. Within each block, the first column includes lender and year-quarter fixed effects, while the second replaces lender fixed effects with lender-year fixed effects. The data span 1994 to 2020. Standard errors are two-way clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

while the second replaces bank fixed effects with bank-year fixed effects. All Appendix Tables for this outcome further report estimates with time-varying lender controls.

Improved outside options predict higher risky credit growth, with non-investment-grade volume growth rising by 1.6 to 3.0 percentage points per standard-deviation increase across the two main specifications, both significant at the 1% level. Total and investment-grade volume growth effects are positive but smaller and not statistically significant. The estimates for non-investment-grade volume growth equal 2.1 to 4.0% of its standard deviation. For comparison, Berrospide and Edge (2024) find that a one percentage point larger stress-test capital buffer lowers committed loan growth by 1.5 percentage points. Our volume response is therefore similar in magnitude to the response associated with a 1.0 to 2.0 percentage point reduction in the capital buffer. Allocating each facility across its lead arrangers, a standard deviation shock reaching all sample lenders for four quarters maps into approximately 8 to 16 billion USD of additional annual risky syndicated loan volume.

The non-investment-grade volume response is robust across an extensive set of checks. The estimate remains virtually unchanged when we add bank i's own employee inflows and outflows as controls (Panel B of Table 1). These controls address the possibility that contemporaneous staffing changes at a given bank are correlated with both our measure of outside options and the bank's lending capacity. The stability of the estimate also speaks against a sorting mechanism whereby outside options induce more talented bankers to depart, leaving less skilled bankers to issue riskier loans. Under such a mechanism, the effect of outside options would operate mainly through realized departures, so controlling for outflows should substantially attenuate the estimated IAT coefficient. Since controlling for the observed number of outflows leaves the estimate virtually unchanged, such sorting and the resulting compositional changes appear to play little role.

A major concern for identification is that coworker networks connect banks exposed to the same cyclical variation in credit demand. For example, a boom in leveraged bank lending could increase both hiring at connected banks and risky lending at the bank in question. We address this concern by generating shift-share control variables that retain the coworker tie weights but replace hiring in connected banks with the level and annual growth of syndicated lending at those banks. The controls cover levels and growth rates of total syndicated lending and of three measures of leveraged lending. These are each defined using spreads of at least 200 basis points, borrowers rated below investment grade or loan purposes associated with buyouts, mergers and acquisitions and recapitalizations. Panel C of Table 1 adds these tie-weighted lending measures jointly and Table A12 shows that results are unchanged under separate inclusion. The coefficient on inflows at ties remains stable, which indicates that granular lending cycles at connected banks do not account for the response in risky loan volumes.

A related concern is that fine-grained demand cycles outside of the financial sector could be affecting bankers' outside options by providing high-paying exit opportunities during real expansions, as highlighted in Axelson and Bond (2015). To address this concern, we generate the proxy variable *inflows at borrowers* (IAB), which measures labor demand at relevant non-financial firms. We weight senior financial hires with an indicator that is equal to one if a bank and a firm have an ongoing lending relationship.[15] Similar to our main measure, the personal interactions between workers at borrower firms and lead arranging banks with ongoing lending relationships are assumed to generate an information channel about labor demand at relevant firms. Appendix Table A13 validates the underlying mobility channel by showing increased departures by bankers to relationship borrowers following inflow shocks at those firms. We then include the IAB measure as a control variable to isolate the effect of outside options from borrower-demand dynamics. Panel D of Table 1 shows that our outside options estimate is not affected by the inclusion of this control.

Further checks are reported in Appendix Table A14. In Panels A through C, we filter for newly originated loans, allocate each facility across its lead arrangers and exclude the 2007 to 2008 financial crisis years, respectively. In Panel D, we account for the network structure of the syndication process. As banks co-arrange deals, senior bankers from two competitor firms interact, forming social ties similar to those created via coworker job moves. We construct *inflows at co-signatories* (IAC), which weights inflows at other lenders with the share of active co-arranged loans with each other lender. It captures exposure to news about outside options in the financial sector at firms where the banker remains within some proximity of the current employer bank. Information about loan de-

[15] The relationships require at least two loans without a material break and the exposure window begins only after the second loan. We remove hires arriving from the lender in question from the hiring shift at the borrower level.

faults of a banker is more likely to reach the new employer firm j if that firm is a frequent co-signatory of i. Similarly, a banker moving to a frequent co-syndicator may remain partly within the former employer's termination threat, since the bank j may be reluctant to jeopardize the ongoing relationship with bank i. IAC should therefore capture outside options that should not affect banker lending behavior, as they do not place bankers beyond the dismissal threat arising from risky lending practices. Consistent with this interpretation, controlling for financial sector labor demand at co-signatory firms does not substantially affect the estimates of our main outside options measure, IAT.

Lastly, we recompute the outside options measure separately from medium-seniority and high-seniority job-to-job hires. The results suggest a consistent pattern, with no systematic difference across seniority groups (Appendix Table A15). We also demonstrate that varying the start and end dates for the predetermined coworker ties does not affect our results, as reported in Appendix Table A16.

Financial Risk. Next, we examine whether outside options predict growth in financial risk at the lending bank and in the systemic risk associated with that bank, measured by VaR and CoVaR. These measures allow us to test whether the change in lending risk generated through non-prime credit origination passes through to an established measure of the bank's tail loss and an established measure of sectoral risk conditional on that bank being in distress. Recall that Value at Risk, VaR, summarizes the tail loss of bank i at a stated confidence level whereas CoVaR summarizes the financial sector's VaR conditional on bank i being in distress at a stated confidence level. We transform the 95% and 99% VaR and CoVaR series into symmetric growth rates and estimate Equation (14) with the same two specifications as for lending volume.

The results are reported in Table 2. Across outcomes, the coefficients are positive and the strongest estimates arise in specifications that absorb time-varying lender heterogeneity through lender-year fixed effects. At the 95% confidence level, a standard-deviation improvement in outside options leads to increases of 0.42 percentage points in VaR and 0.43 percentage points in CoVaR in the lender-year specification. At the 99% confidence level, the corresponding estimates rise to 0.74 and 0.73 percentage points, respectively. Since the dependent variables are quarterly midpoint growth rates multiplied by 100, the estimates are approximately equal to conventional percentage point growth. On the

Table 2: Effect of Outside Options on Changes in Financial Risk

	VaR 95%		CoVaR 95%		VaR 99%		CoVaR 99%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Baseline								
IAT	0.192	0.425	0.208	0.425*	0.325**	0.740**	0.331***	0.730***
	(0.184)	(0.287)	(0.144)	(0.237)	(0.144)	(0.288)	(0.117)	(0.253)
Panel B. Controlling for In- and Outflows								
IAT	0.221	0.405	0.259*	0.397*	0.358**	0.721**	0.376***	0.705***
	(0.182)	(0.284)	(0.144)	(0.230)	(0.146)	(0.282)	(0.120)	(0.245)
Inflows to i	X	X	X	X	X	X	X	X
Outflows from i	X	X	X	X	X	X	X	X
Panel C. Controlling for Lending at Ties								
IAT	0.264	0.515*	0.278*	0.497**	0.398**	0.811***	0.398**	0.785***
	(0.199)	(0.291)	(0.156)	(0.239)	(0.187)	(0.304)	(0.162)	(0.263)
Lending at ties, level	X	X	X	X	X	X	X	X
Lending at ties, growth	X	X	X	X	X	X	X	X
Panel D. Controlling for Inflows at Borrowers (IAB)								
IAT	0.192	0.433	0.208	0.425*	0.325**	0.750**	0.331***	0.734***
	(0.184)	(0.287)	(0.144)	(0.237)	(0.143)	(0.287)	(0.117)	(0.253)
IAB	X	X	X	X	X	X	X	X
Lender FE	X		X		X		X	
Lender × Year FE		X		X		X		X
Year-Quarter FE	X	X	X	X	X	X	X	X
Observations	18,680	18,499	18,680	18,499	18,680	18,499	18,680	18,499

Notes: The table reports OLS estimates for midpoint growth rates in VaR and CoVaR in percentage points. Panel A reports the baseline estimates. Panel B controls jointly for lender inflows and outflows. Panel C jointly controls for exposure-weighted levels and annual growth rates of four lending measures at connected banks. These measures cover total syndicated lending and leveraged lending defined using spreads of at least 200 basis points, borrowers rated below investment grade or loan purposes associated with buyouts, mergers and acquisitions and recapitalizations. Panel D controls for standardized Inflows at Borrowers, *IAB*. The outcomes are VaR at the 95% confidence level in Columns (1) and (2), CoVaR at the 95% confidence level in Columns (3) and (4), VaR at the 99% confidence level in Columns (5) and (6) and CoVaR at the 99% confidence level in Columns (7) and (8). Within each outcome block, the first column includes lender and year-quarter fixed effects, while the second replaces lender fixed effects with lender-year fixed effects. The data are at quarterly frequency and span 1994 to 2009. Standard errors are two-way clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

estimation samples, the lender-year coefficients at the 99th percentile equal 3.6% of the standard deviation of VaR growth and 3.7% of the standard deviation of CoVaR growth. The 99th-percentile responses also equal about 5% of mean quarterly VaR and CoVaR growth during 2007 and 2008. Despite being modest relative to surges during the financial crisis, these effects are nontrivial relative to average quarterly risk growth even during 2007 and 2008. The effects are modest in magnitude, but the fact that they are detectable at the bank level suggests that variation in outside options translates into economically meaningful changes in financial risk.

The financial risk response is robust across the same set of checks as the loan volume results, presented in Table 2 and a series of Appendix tables. As panel B shows, the estimates remain virtually unchanged when we add bank i's own employee inflows and outflows as controls. Panel C of Table 2 adds the tie-weighted levels and annual growth rates of total and leveraged lending at connected banks jointly. Appendix Table A17 adds each of the four lending definitions separately. The coefficients on inflows at ties remain stable or increase, which indicates that granular lending cycles at connected banks do not account for the responses in VaR and CoVaR. Panel D of Table 2 controls for IAB, with estimates virtually unchanged, indicating that labor demand at relevant non-financial firms does not account for the financial risk response.

Further checks are reported in Appendix Table A18. Panel A accounts for the network structure of the syndication process by controlling for inflows at co-signatories. Panel B excludes the 2007 to 2008 financial crisis years. The estimates remain positive in both cases and when we add time-varying lender controls. Lastly, we recompute the outside options measure separately from medium-seniority and high-seniority job-to-job hires. The results show no systematic difference across seniority groups (Appendix Table A19). We also demonstrate that varying the start and end dates for the predetermined coworker ties does not affect our results, as reported in Appendix Table A20.

Taken together, the VaR and CoVaR responses suggest that the additional tail risk associated with outside options is not confined to the originating bank. The increase in bank tail risk is accompanied by a similarly sized increase in systemic tail risk, consistent with riskier lending generating interconnected exposure rather than purely idiosyncratic risk. Syndicated lending provides several potential channels for such dispersion. Credit risk is shared by design across participating banks at origination and can spread further as tranches are securitized and traded in secondary markets. The concentration of the responses for both variables at the 99th percentile also suggests that the credit expansion that we observe is particularly relevant for extreme downside outcomes and for financial stability.

Effect Dynamics. To examine the dynamics of the lender-level effects, Figure 4 reports results from regressing cumulative changes in inverse hyperbolic sine transformations of risky loan volume, VaR and CoVaR at the 99th percentile on inflows at ties across the different fixed-effects specifications. Prior to the shock, the coefficients are small and insignificant. On impact, all outcomes show positive responses, with statistically significant coefficients in the first quarter. At later horizons, the coefficients remain elevated but are estimated less precisely. Overall, the dynamics indicate an immediate increase in risk-taking, while the positive but imprecise later estimates are consistent with a potentially more persistent response.

5.2 Borrower Risk

We now examine the loan choices underlying this aggregate response. The analysis at the loan level allows us to determine whether banks shift borrower selection toward greater risk, compare loans exposed to similar demand conditions and assess whether the additional ex-ante risk is compensated in prices and realized in subsequent borrower performance. Given a bank i issuing a loan l to borrower b in year-quarter t, the loan-level specification is given by:

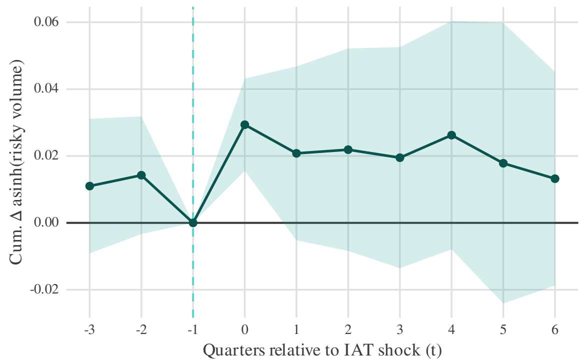
$$y_{bilt} = \beta\, InflowsAtTies_{it} + \Gamma V_{it} + \Theta W_{bt} + \Pi Z_{ilt} + \alpha_{i,yr} + \lambda_t + \epsilon_{bilt}, \tag{15}$$

where y_{bilt} is a measure of credit risk, proxied by the borrower's credit rating. As before, we regress the outcome on inflows at ties, with lender-level controls and fixed effects at the lender-year and year-quarter level. The loan-level specification additionally allows us to control for the same balance-sheet variables on the borrower side, W_{bt} and for loan-level covariates Z_{ilt}, detailed in the respective table notes.

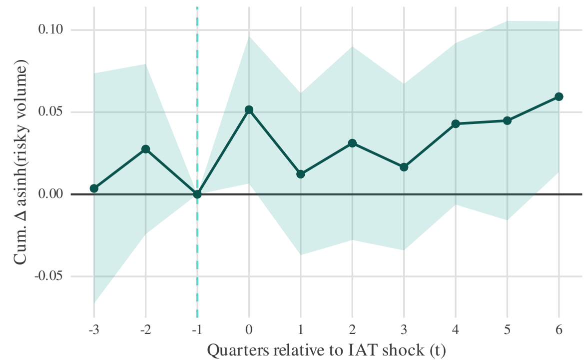
Ex-Ante Risk. The results from estimating linear probability models are presented in Table 3. Given that the outcome is a borrower-level indicator equal to one if the borrower is rated below investment grade by S&P, multiplied by 100, a positive coefficient suggests a percentage point shift toward nominally riskier borrowers. $InflowsAtTies_{it}$ is standardized and all columns include the full set of borrower, lender and loan controls. Column (1) is the baseline specification of Equation (15) with lender and year-

Figure 4: Dynamic Effects of Risky Loan Volume Growth and Financial Risk

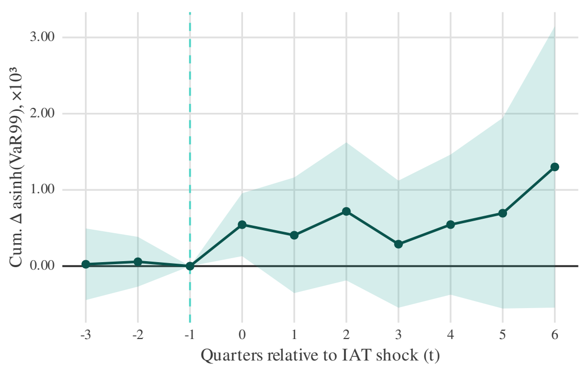
(a) Risky loan volume, lender and year-quarter FE



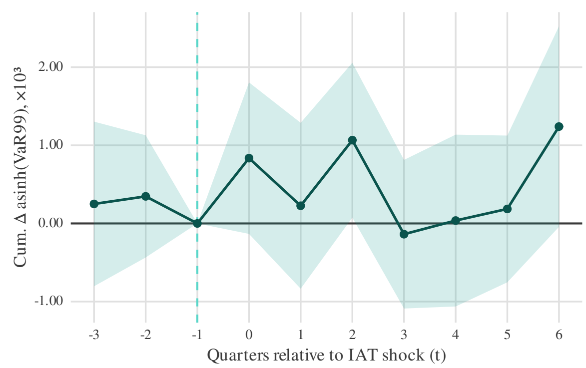
(b) Risky loan volume, lender-year and year-quarter FE



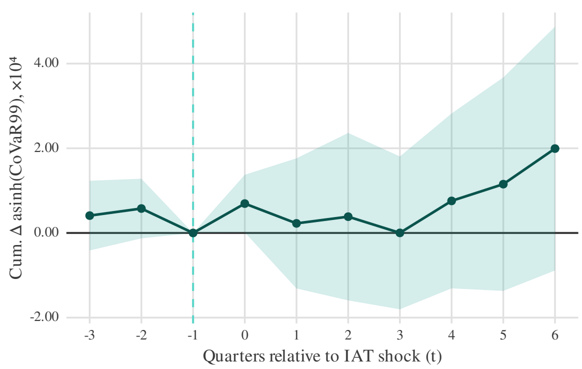
(c) VaR99, lender and year-quarter FE



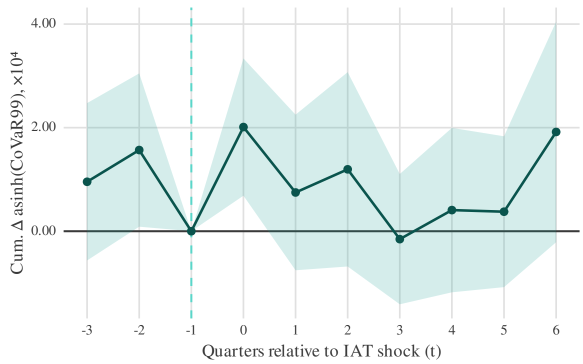
(d) VaR99, lender-year and year-quarter FE



(e) CoVaR99, lender and year-quarter FE



(f) CoVaR99, lender-year and year-quarter FE



Notes: Each point is the coefficient from a separate regression of the cumulative inverse hyperbolic sine change from quarter $t-1$ to the indicated horizon on standardized inflows at ties. The reference quarter $t-1$ is normalized to zero. Shaded bands are 95% confidence intervals based on two-way clustered standard errors at the lender and year-quarter levels.

quarter fixed effects included. A standard-deviation increase in inflows at ties raises the probability that a borrower is below investment grade by about half a percentage point. Columns (2) to (5) replace the lender fixed effect with lender-year fixed effects. Column (3) adds borrower-sector-by-year-quarter fixed effects, Column (4) adds borrower-state-by-year-quarter fixed effects and Column (5) includes both sets, which absorb time-varying demand-side factors (Huang et al., 2024, 2025). The baseline coefficient in panel A is stable throughout and increases in magnitude under the fully saturated specification in Column (5), where it reaches 1.3 percentage points per standard deviation. Across the five specifications, the estimates equal 1.0 to 2.8% of the outcome standard deviation. These estimates show that improved outside options shift borrower selection toward firms with observably greater ex-ante credit risk.

Panels B to D of Table 3 apply the same identification checks as the tables for outcomes at the lender level. Respectively, the results indicate that staffing changes at the lending bank, granular lending cycles at connected banks and labor demand at relevant non-financial firms do not account for the shift in borrower risk. The coefficient remains stable and significant when we control jointly for the lending bank's employee inflows and outflows in Panel B. Panel C adds the tie-weighted levels and annual growth rates of total and leveraged lending at connected banks. Appendix Table A21 adds each lending definition separately and yields similar estimates. Panel D of Table 3 controls for inflows at borrowers, with estimates virtually unchanged.

Additional checks are reported in Appendix Table A22. The coefficient remains positive and significant when we control for the number of lenders in the syndicate and inflows at co-signatories, restrict the sample to newly originated loans, exclude 2007 and 2008 or winsorize the outside options measure at the 1st and 99th percentiles. The response is moderately larger when outside options are constructed from hiring of more senior bankers at connected banks, although the differences across seniority groups are imprecisely estimated (Appendix Table A23). Varying the start and end dates of the predetermined coworker ties also leaves the results unchanged (Appendix Table A24).

We expand on the robustness exercises targeting concerns that time-varying credit demand and lending conditions at coworker-tied banks may affect both their hiring behavior and the focal lender's borrower composition at the same time. As discussed above, an increase in demand for corporate or leveraged credit in markets served by connected

Table 3: Effect of Outside Options on Borrower Risk

	Below-Investment-Grade Borrower, percentage points				
	(1)	(2)	(3)	(4)	(5)
Panel A. Baseline					
IAT	0.475***	0.583***	0.622***	1.280***	1.258***
	(0.147)	(0.178)	(0.176)	(0.341)	(0.382)
Panel B. Controlling for In- and Outflows					
IAT	0.538***	0.658***	0.689***	1.368***	1.332***
	(0.153)	(0.180)	(0.183)	(0.366)	(0.412)
Inflows to i	X	X	X	X	X
Outflows from i	X	X	X	X	X
Panel C. Controlling for Lending at Ties					
IAT	0.571***	0.565***	0.585***	1.229***	1.167***
	(0.153)	(0.180)	(0.178)	(0.365)	(0.389)
Lending at ties, level	X	X	X	X	X
Lending at ties, growth	X	X	X	X	X
Panel D. Controlling for Inflows at Borrowers (IAB)					
IAT	0.476***	0.584***	0.625***	1.281***	1.266***
	(0.145)	(0.183)	(0.185)	(0.343)	(0.376)
IAB	X	X	X	X	X
Lender FE	X				
Lender × Year FE		X	X	X	X
Year-Quarter FE	X	X			
Borrower Sector × Year-Quarter FE			X		X
Borrower State × Year-Quarter FE				X	X
Lender, Borrower, Loan Controls	X	X	X	X	X
Observations	55,327	55,278	55,223	50,082	50,045

Notes: The table reports regressions at the loan level of Equation (15). The dependent variable is an indicator equal to one if the borrower is rated below investment grade by S&P, multiplied by 100. Panel A reports the baseline estimates. Panel B controls jointly for lender inflows and outflows. Panel C jointly controls for exposure-weighted levels and annual growth rates of four lending measures at connected banks. These measures cover total syndicated lending and leveraged lending defined using spreads of at least 200 basis points, borrowers rated below investment grade or loan purposes associated with buyouts, mergers and acquisitions and recapitalizations. Panel D controls for standardized Inflows at Borrowers, IAB. All columns include lender, borrower and loan controls. Column (1) includes lender and year-quarter fixed effects. Columns (2) to (5) include lender-year fixed effects. Column (3) adds borrower-sector-year-quarter fixed effects, Column (4) adds borrower-state-year-quarter fixed effects and Column (5) includes both. The data span 1994 to 2020. Standard errors are two-way clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

banks j could lead those banks to expand lending and to hire additional bankers at the same time. If lender i is exposed to the same demand conditions, inflows at ties could

Table 4: Robustness to Segment-Time Confounders

	Non-Prime Borrower, percentage points			
	NAICS-2		NAICS-3	
	(1)	(2)	(3)	(4)
IAT	0.358**	0.386***	0.283**	0.401***
	(0.164)	(0.135)	(0.140)	(0.133)
Exposure-weighted Segment-Year inflows		X		X
Lender, Borrower, Loan Controls	X	X	X	X
Lender + Year-Quarter FE	X	X	X	X
Segment × year FE	X		X	
Observations	52,070	52,070	52,069	52,070

Notes: The dependent variable is a below-investment-grade borrower indicator multiplied by 100. Columns (1) and (2) use two-digit NAICS segments, while Columns (3) and (4) use three-digit NAICS segments. Columns (1) and (3) add fixed effects for the lender's dominant connected-bank industry segment interacted with year. Columns (2) and (4) add an exposure-weighted control for inflows in the industry segments of firms connected to lender i. All columns include borrower, lender and loan controls as well as lender and year-quarter fixed effects. Standard errors are two-way clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

then proxy for a common lending cycle rather than changes in bankers' outside options. In addition to controlling for lending at ties and inflows at borrowers, we conduct an additional check that captures such conditions at the industry-segment level. If a lender's network is disproportionately connected to banks serving particular industries, hiring at those connected banks may covary with industry-level credit demand that also affects the lender's own loan issuance. We implement this test in two ways. First, we identify the industry segment receiving the largest share of each bank's network weight and absorb year-specific fixed effects for that dominant segment. This allows lenders whose networks are concentrated in different industries to follow different lending trajectories over time, separately for two- and three-digit NAICS segments. Second, we calculate total hiring in each connected bank's industry segment and weight it by the lender's network shares. We include this exposure-weighted segment-year inflows measure as a control, absorbing industry-level hiring conditions reaching the lender through its full network. We implement both approaches at the two- and three-digit NAICS levels. The coefficient on inflows at ties remains positive and stable across these specifications (Table 4).

The result also extends to alternative measures of borrower risk. Table 5 replaces the indicator for borrowers below investment grade with continuous risk scores based on issuer-level Compustat S&P ratings in Panel A, issue-level Mergent FISD median bond ratings in Panel B, as well as borrower book leverage in Panel C. The coefficient on inflows at ties is positive across every specification and outcome. Better outside options are therefore associated with borrowers that have weaker credit ratings and higher leverage.

Although our tie weights are predetermined relative to current hiring, changes in network composition can still contribute to variation in the outside options measure. If those changes are correlated with shifts in lending behavior, the baseline estimates could partly reflect changing exposure rather than hiring shocks at connected banks. We address this concern in two steps, with results reported in Table A25. First, we estimate the specification in first differences, with the change in the share of non-investment-grade loans by a given bank in a given year-quarter as the outcome for both columns. In the first column, we use changes in our standard outside options measure, IAT, as the main regressor. In the second column, we further replace the change in the baseline measure with a fixed-exposure first-difference shift-share measure, $\sum_j w_{ij,t-1} \Delta Inflows_{jt}$ (Borusyak et al., 2022), which holds network composition fixed at its prior quarter level and isolates variation from changes, rather than levels, in connected-bank hiring. The shift toward riskier borrowers remains positive in both specifications.

Next, we investigate whether the response of borrower ratings depends on the ease of job-to-job transitions. To this end, we exploit variation in the enforceability of non-compete agreements (NCAs), which restrict job mobility toward direct competitors within the same state (Johnson et al., 2025). When state courts issue decisions that overturn precedent, they create changes in enforceability over time that we utilize. When enforceability decreases in the bank's headquarters state, bankers face fewer constraints on exercising outside options. We interact our measure with a state-level enforceability index built from events reported by Mueller (2026), assigning them to the lender headquarter state. Columns (1) and (2) of Table 6 interact outside options with a signed index that equals 1 after enforcement increases and -1 after enforcement decreases. The interaction is negative and statistically significant at the 5% level, with and without state-year fixed effects. Columns (3) and (4) estimate the two directions separately. Since the sample contains no loans following a weakening event that was not preceded by a strength-

Table 5: Alternative Measures of Borrower Risk

	(1)	(2)	(3)	(4)
Panel A. Compustat S&P Borrower-Risk Score, 0–100				
IAT	0.173**	0.401***	0.417***	0.715***
	(0.069)	(0.071)	(0.072)	(0.138)
Observations	55,327	55,278	55,223	50,045
Panel B. FISD Borrower-Risk Score, 0–100				
IAT	0.481***	0.334*	0.321*	0.389**
	(0.161)	(0.166)	(0.182)	(0.182)
Observations	30,144	30,091	30,022	28,078
Panel C. Book Leverage, percentage points				
IAT	0.143*	0.270***	0.246***	0.515***
	(0.077)	(0.048)	(0.048)	(0.160)
Observations	55,327	55,278	55,223	50,045
Lender FE	X			
Year-Quarter FE	X	X		
Lender × Year FE		X	X	X
Borrower Sector × Year-Quarter FE			X	X
Borrower State × Year-Quarter FE				X
Lender, Borrower, Loan Controls	X	X	X	X

Notes: The table re-estimates the four borrower risk specifications at the loan level using alternative outcomes. Panel A uses a continuous Compustat S&P risk score, Panel B uses contemporaneous Mergent FISD bond ratings and Panel C uses borrower book leverage at origination. A positive coefficient indicates greater borrower risk. IAT is standardized. All columns include lender, borrower and loan controls. Column (1) includes lender and year-quarter fixed effects. Column (2) replaces lender fixed effects with lender-year fixed effects. Column (3) adds borrower-sector-by-year-quarter fixed effects, while Column (4) adds borrower-state-by-year-quarter fixed effects to the specification in Column (3). Standard errors are two-way clustered at the lender and year-quarter levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

ening event, our power to detect the enforcement decrease effect is limited. Indeed, the interaction with stronger enforcement is negative and statistically significant, while the interaction following weaker enforcement is positive but imprecisely estimated. The results therefore show that stronger enforcement attenuates the association between outside options and borrower risk. Overall, the evidence is consistent with the notion that the response in borrower risk is conditional on the ability of bankers to exercise their out-

Table 6: Outside Options and Borrower Risk Following Changes in NCA Enforceability

Outcome	Non-prime Borrower (ex ante, pp)			
	(1)	(2)	(3)	(4)
IAT	1.322	1.322	1.298	1.298
	(2.074)	(2.081)	(2.075)	(2.082)
IAT × NCA Enforceability Index	-5.351**	-5.351**		
	(2.255)	(2.262)		
IAT × Stronger Enforcement			-5.352**	-5.352**
			(2.255)	(2.262)
IAT × Weaker Enforcement			79.479	79.479
			(47.098)	(47.251)
Lender × Year FE	X	X	X	X
Year-Quarter FE	X	X	X	X
HQ State × Year FE		X		X
Lender, Borrower, Loan Controls	X	X	X	X
Observations	26,845	26,845	26,845	26,845

Notes: The table reports estimates at the loan level based on Column (1) of Table 3. The dependent variable is an indicator for a borrower rated below investment grade multiplied by 100. In Columns (1) and (2), the enforcement index equals 1 after stronger enforcement, −1 after weaker enforcement and 0 otherwise. Columns (3) and (4) include separate IAT interactions with indicators for stronger and weaker enforcement. Every column includes lender-year and year-quarter fixed effects. Columns (2) and (4) also include headquarters-state-by-year fixed effects. All regressions include borrower, lender and loan controls. Standard errors are two-way clustered by lender and year-quarter. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

side options and inconsistent with explanations based solely on correlated hiring, lending conditions or other shocks that do not vary with the enforceability of non-compete agreements.

An important question is whether the shift toward riskier borrowers reflects a genuine increase in uncompensated risk-taking rather than standard yield seeking by banks. Under yield seeking, the decline in ratings should be compensated by higher spreads. We test this by regressing the log all-in spread drawn, the standard measure of loan pricing, on inflows at ties, conditional on the full set of borrower, lender and loan controls and the same series of fixed effects as in Table 3. As reported in Table 7, the coefficient ranges from −0.002 to 0.003 across the four specifications and is not statistically significant in any column. At the mean spread of about 225 basis points, the point estimates imply changes between −0.4 and 0.6 basis points. The largest 95% upper confidence bound is 2.8 basis points, equivalent to 1.7% of the outcome standard deviation. Banks thus take on riskier borrowers without demanding significantly higher compensation, which is difficult to reconcile with yield seeking.

Ex-Post Risk. So far, we have measured borrower risk at origination. An important follow-up question is whether the shift toward riskier borrowers translates into worse ex-post credit outcomes rather than solely reflecting a change in the composition of ex-ante ratings. We track two realized borrower outcomes over the three years following each loan event. The first is subsequent downgrades of the borrower's bonds from Mergent FISD records of Moody's, S&P and Fitch rating actions. The second is the spread on the borrower's next syndicated loan, conditional on the spread of the current loan.

Table 8 reports results for these outcomes in our baseline panel specification, with lender and year-quarter fixed effects and the full set of controls. Loans originated when bankers at the lending institution face better outside options are followed by more downgrades, with the effect being more pronounced in the tail of the outcome distribution. The likelihood of any downgrade rises by 0.8 percentage points in Column (1) and is statistically significant at the 10% level, while the likelihoods of two or more (Column (2)) and three or more (Column (3)) downgrade actions rise by about 1.3 percentage points per standard deviation and are statistically significant at the 5% level. The effects on at least one, two and three downgrades equal 1.6, 2.7 and 2.9% of their respective outcome standard deviations. The latter two estimates raise the outcome probabilities by 4.0 and 4.7% relative to their means. These magnitudes are similar to the 5% increase in the ex-post default probability that Jiménez et al. (2014) find for risky loans after a one percentage point reduction in the overnight interest rate at low-capital banks. In Column (4), we document that the borrower's next loan is priced roughly 1% higher in response to better outside options, conditional on the spread of the initial loan. The higher refinancing spread is consistent with lenders assessing the borrower as riskier in the future. The repricing coefficient equals 1.4% of the outcome standard deviation and about 2 basis points at the mean next-loan spread.

Table 7: Outside Options and Loan Pricing

	All-In Spread Drawn (log bps)			
	(1)	(2)	(3)	(4)
IAT	0.003	-0.001	-0.001	-0.002
	(0.005)	(0.002)	(0.001)	(0.003)
Lender FE	X			
Year-Quarter FE	X	X	X	X
Lender × Year FE		X	X	X
Borrower Sector × Year FE			X	
Borrower Industry × Year FE				X
Lender, Borrower, Loan Controls	X	X	X	X
Observations	66,115	66,048	65,998	65,850

Notes: The dependent variable is the log all-in spread drawn. IAT is standardized and all columns include borrower, lender and loan controls. Column (1) includes lender and year-quarter fixed effects. Column (2) replaces lender fixed effects with lender-year fixed effects. Columns (3) and (4) add borrower-sector-by-year and borrower-industry-by-year fixed effects. The sample spans 1994 to 2020. Standard errors are two-way clustered by lender and year-quarter. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Together with the lender-level evidence above, these results show that improved outside options lead banks to expand credit toward riskier borrowers, with a detectable deterioration of realized borrower outcomes. The estimated coefficients are moderate in magnitude but may be attenuated for several reasons. First, by estimating effects at the bank level, we average across all investment bankers, including those who are unresponsive to outside options because of low observed productivity, niche specialization or strong firm-specific attachments (Caldwell et al., 2025). Second, our identification strategy removes cyclical variation in outside options, which represents a substantial share of the overall variation and is likely the component to which bankers respond most.[16] Third, our measure does not capture news about labor demand at other firms that is transmitted outside personal networks, such as public job postings, positions at non-connected banks or opportunities outside the financial industry. Thus, our results reflect the average response to variation in one plausibly exogenous component of outside options.

[16]Year-quarter fixed effects explain around 39% of the overall variation in inflows at ties. Adding bank fixed effects increases the R^2 by only 8 percentage points.

Table 8: Ex-Post Borrower Deterioration

Ex-post outcome	≥1 Downgrade (pp)	≥2 Downgrades (pp)	≥3 Downgrades (pp)	Next-Loan Spread
	Subsequent bond downgrades (3y; pp)			Next loan (3y)
	(1)	(2)	(3)	(4)
IAT	0.755*	1.247**	1.281**	0.009**
	(0.446)	(0.499)	(0.573)	(0.003)
Current Loan Spread				0.531***
				(0.022)
Lender FE	X	X	X	X
Year-Quarter FE	X	X	X	X
Lender, Borrower, Loan Controls	X	X	X	X
Observations	29,287	29,287	29,287	40,822

Notes: The table reports results from a regression of ex-post borrower deterioration on $InflowsAtTies_{it}$ at loan origination, estimating Equation (15) at the loan level with lender and year-quarter fixed effects and the full set of borrower, lender and loan controls. In Columns (1)–(3), the outcome equals one if the borrower's outstanding bonds receive at least one, two or three rating downgrades, respectively, from Moody's, S&P or Fitch within three years of origination (Mergent FISD). The sample includes loans for which the borrower has a rated bond outstanding at origination. In Column (4), the outcome is the inverse hyperbolic sine of the all-in spread drawn, in basis points, on the borrower's next syndicated loan within three years, controlling for the current loan's spread. $InflowsAtTies_{it}$ is standardized to unit variance. The downgrade estimates are unchanged when controlling for the number of the borrower's outstanding bonds. Standard errors are two-way clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6 Mechanism

This section provides individual-level evidence in favor of the discipline dilution mechanism described in the conceptual framework. We first establish that the ex-post rating result is present among loans linked to named signing bankers. We then ask whether outside options weaken the separation penalty following poor loan performance, as predicted by Equation (9), and whether the risk response is concentrated among younger bankers, whose higher overall mobility makes outside opportunities more relevant. The final subsection shows complementary evidence on financial advisors, for which we document consistent results on a separate measure of misaligned behavior and the dilution of dismissal discipline.

6.1 Evidence on Discipline Dilution

We are able to match a subset of loans to the individual bankers who signed them according to a procedure described in Section 3 and recover these bankers' employment histories. For each matched loan we observe the borrower's subsequent rating trajectory, as well as the signing banker's subsequent career at the lending bank.

We first replicate the loan-level result by estimating Equation (15) in the individual banker sample. Table 9 shows the results using ex-post loan performance as the outcome. A standard-deviation increase in IAT raises the probability of any downgrade by 18.6 percentage points within two years and 19.8 percentage points within three years. The corresponding estimates are 13.1 and 13.8 percentage points after adding lender controls. In the specifications with lender controls, these effects equal 35% and 34% of the standard deviations of the respective dependent variables. The same shock also raises the maximum rating deterioration within two years by 0.30 notches, an increase of 31% of the outcome standard deviation. These estimates reproduce the deterioration in ex-post loan performance from the full loan sample within the subset of loans matched to individual bankers, supporting its use for the subsequent banker career and heterogeneity analyses. The effects are larger in this sample and remain economically large across both the incidence and severity of downgrades, with similar estimates over two- and three-year horizons. The larger magnitudes may partly reflect selection into the matched sample.

We then investigate the implication of Equation (9), which predicts that the separation penalty following poor performance falls as outside options improve. To test this idea, we leverage the information on job separations from the employment histories. For signer s and loan ℓ, we estimate

$$Separation_{s\ell} = \beta_1 \, Bad_{\ell} + \beta_2 \, InflowsAtTies_{it} + \beta_3 \left(Bad_{\ell} \times InflowsAtTies_{it} \right) + \alpha_{i,yr} + \lambda_t + \varepsilon_{s\ell}, \quad (16)$$

where $Separation_{s\ell}$ is an indicator for whether the banker separated from the bank within a specified time period, Bad_{ℓ} indicates that the borrower's bonds were downgraded within two years of origination and inflows at ties are measured over the window in which the outcome materializes and the retention decision is made. All other variables and indices are defined as before.

Table 9: Effect of Outside Options on Borrower Deterioration at the Individual Level

	Any Downgrade (2y pp)		Any Downgrade (3y pp)		Number of Downgrades (2y pp)	
	(1)	(2)	(3)	(4)	(5)	(6)
IAT	18.585***	13.092**	19.754***	13.783***	0.270***	0.301**
	(3.688)	(5.147)	(4.268)	(3.264)	(0.072)	(0.141)
Lender FE	X	X	X	X	X	X
Origination year-quarter FE	X	X	X	X	X	X
Lender controls		X		X		X
Observations	738	438	741	440	738	438

Notes: The sample contains syndicated loans matched to a signing banker. IAT is standardized and measured in the loan origination quarter. The rating outcomes use Compustat's issuer-level S&P ratings. Any Downgrade equals 100 if the borrower's rating is lower at any point during the stated horizon following origination and zero otherwise. Number of Downgrades is the maximum number of rating notches lost during the 24 months following origination. Columns (1), (3) and (5) include lender and origination year-quarter fixed effects. Columns (2), (4) and (6) add lender controls. Lender controls are inverse hyperbolic sine transformations of total assets, net income, EBIT, short- and long-term debt, employment, liabilities, common equity and capital expenditures. Standard errors in parentheses are clustered by lender and origination year-quarter. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results are reported in Table 10. The positive baseline coefficient on inflows at ties for job-to-job moves confirms that the measure predicts mobility in this smaller sample. Consistent with Gao et al. (2020), poor loan performance is predictive of adverse career outcomes. After a bad outcome on a signed loan, bankers are 7 to 11 percentage points more likely to separate from the bank within two to three years, with estimates significant in the specifications that include lender controls. The interaction β_3 is negative in all columns and statistically significant throughout. The interaction implies that a standard-deviation improvement in outside options offsets between 41% and 86% of the respective career penalties in the specifications with lender controls. Together, the coefficients show that better outside options predict more mobility and a smaller observed separation penalty following poor loan outcomes, as implied by the discipline dilution channel.

Next, we empirically document the age heterogeneity in job mobility among individual signing bankers discussed in the conceptual framework. Table 11 shows that each additional year of age lowers the probability of separating within two years by 1.3 percentage points and within three years by 1.8 percentage points, against base rates of 26

Table 10: Outside Options and the Separation Penalty for Poor Loan Outcomes

	Job Separation (2 Years, pp)		Job Separation (3 Years, pp)		Job to Job Move (2 Years, pp)	
	(1)	(2)	(3)	(4)	(5)	(6)
Bad Outcome	4.156	10.307**	2.244	7.326**	3.410	10.624**
	(4.343)	(4.223)	(3.546)	(3.234)	(4.406)	(4.300)
IAT	3.459	6.026	8.160*	11.416*	8.097***	8.819*
	(2.798)	(4.941)	(4.514)	(6.496)	(2.916)	(4.663)
Bad Outcome × IAT	-7.391***	-8.228**	-4.730***	-6.311*	-5.236***	-4.396*
	(2.673)	(3.910)	(1.625)	(3.394)	(1.737)	(2.526)
Lender FE	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X
Lender Controls		X		X		X
Observations	806	499	806	499	806	499

Notes: The table estimates Equation (16) on loans matched to their signing banker. *Bad Outcome* equals one if the borrower's outstanding bonds were downgraded by Moody's, S&P or Fitch within two years of origination (Mergent FISD). Each outcome indicator is multiplied by 100 before estimation, so coefficients are in percentage points. The indicators identify whether the banker separated from the lending bank within two years of origination (Columns 1–2), separated within three years (Columns 3–4) or moved to another employer within two years (Columns 5–6). $InflowsAtTies$ is standardized and measured during the second year after origination, the period in which the retention decision is made. Lender controls are the inverse hyperbolic sine transformations of total assets, net income, EBIT, capital expenditure, total liabilities, short- and long-term debt, equity and number of employees. Standard errors are two-way clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

and 36 percent. Job-to-job moves show a similar pattern. Over the average age gap between a vice president and a senior managing director of 15 years, this amounts to a difference in mobility of 20 to 27 percentage points. Labor-market transitions are thus concentrated among young bankers.

Within the conceptual framework, the lower mobility for older bankers implies that outside options should have a smaller effect on their behavior, as they are less likely to have a dominating offer to fall back on. The framework therefore predicts a weaker risk response among older signers. Table 12 tests this prediction by regressing indicators of ex-post deterioration on inflows at ties, measured at origination, interacted with the signing banker's age. Columns (1) and (2) indicate any downgrade action on the borrower's outstanding bonds within two years, Columns (3) and (4) extend the horizon to three years and Columns (5) and (6) indicate a severe outcome, defined as at least three downgrade actions within two years.

Table 11: Banker Age and Labor Market Transitions

	Separation (2y pp)		Separation (3y pp)		Job-to-Job Move (2y pp)	
	(1)	(2)	(3)	(4)	(5)	(6)
Bad Outcome	6.881	-6.600	-9.057	-19.742	18.481	19.603
	(25.254)	(35.695)	(21.086)	(30.355)	(22.257)	(27.810)
Age	-1.282***	-1.266***	-1.784***	-1.769***	-1.322***	-1.379***
	(0.206)	(0.385)	(0.174)	(0.484)	(0.196)	(0.352)
Bad Outcome × Age	-0.086	0.334	0.293	0.624	-0.365	-0.261
	(0.501)	(0.766)	(0.450)	(0.690)	(0.446)	(0.595)
Lender FE	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X
Lender Controls		X		X		X
Observations	776	471	776	471	776	471

Notes: The table regresses the signing banker's subsequent labor market transitions on the banker's age, using the sample of loans matched to individual bankers. Each dependent-variable indicator is multiplied by 100 before estimation, so coefficients are in percentage points. The indicators identify whether the banker separated from the lending bank within two years of loan origination (Columns 1–2), within three years (Columns 3–4) or moved to a job at another employer within two years (Columns 5–6). Separations are constructed from the employment-history data and account for right-censoring. *Bad Outcome* equals one if the borrower's outstanding bonds were downgraded by Moody's, S&P or Fitch within two years of origination (Mergent FISD). Lender controls are the inverse hyperbolic sine transformations of total assets, net income, EBIT, capital expenditure, total liabilities, short- and long-term debt, equity and number of employees. Standard errors are two-way clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Inflows at ties enter positively in all six specifications and four of the six estimates are statistically significant at least at the 10% level. The coefficient of the IAT interaction with age is negative and statistically significant throughout, both with and without lender controls. At age 30, the predicted risk responses to a standard-deviation improvement in outside options range from 15.0 to 19.5 percentage points across the three deterioration measures in the specifications with lender controls. At age 45, the corresponding predictions range from 1.3 to 9.9 percentage points, implying that for those senior bankers the outside options response is reduced by between 49% and 91%. The estimated response is concentrated among bankers young enough to move, a pattern that is not consistent

Table 12: Ex-Post Deterioration and Outside Options by Banker Age

	Any Downgrade Action (2y pp)		Any Downgrade Action (3y pp)		Severe Downgrade Action (2y pp)	
	(1)	(2)	(3)	(4)	(5)	(6)
IAT	9.545	18.053***	14.340*	14.956	10.227*	19.489*
	(6.969)	(6.072)	(7.113)	(9.125)	(5.543)	(9.749)
Age	0.307*	0.199	0.093	-0.061	0.135	0.186
	(0.179)	(0.300)	(0.220)	(0.296)	(0.181)	(0.205)
IAT × Age	-0.842**	-0.967***	-0.854**	-0.912*	-0.439**	-0.639*
	(0.326)	(0.319)	(0.329)	(0.480)	(0.205)	(0.351)
Lender FE	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X
Lender Controls		X		X		X
Observations	734	455	750	466	666	408

Notes: The table reports results from a regression of ex-post deterioration on $InflowsAtTies_{it}$ interacted with the signing banker's age in the sample of loans matched to individual bankers. Each deterioration indicator is multiplied by 100 before estimation, so coefficients are in percentage points. The indicators identify whether the borrower's outstanding bonds received any downgrade action from Moody's, S&P or Fitch within two years of origination (Columns 1–2), received any downgrade action within three years (Columns 3–4) or experienced at least three downgrade actions within two years (Columns 5–6). $InflowsAtTies_{it}$ is standardized and measured in the loan origination quarter. Banker age is measured at origination and centered at 30. Within each outcome pair, the first column includes lender and year-quarter fixed effects, while the second adds lender controls. Lender controls are the inverse hyperbolic sine transformations of total assets, net income, EBIT, capital expenditure, total liabilities, short- and long-term debt, equity and number of employees. Standard errors are two-way clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

with alternative explanations of senior poaching and team lift-outs, since those accounts would predict a stronger response among more senior bankers.

6.2 Evidence on Advisor Misconduct

We provide complementary evidence in a related setting with agency frictions, namely the market for financial advisors. The setting adds two features to the previous analysis. Conceptually, advisor misconduct identifies behavior that harms clients and employers more directly than an externally observed increase in credit risk. Moreover, the information on approximately 140,000 individually linked advisors provides enough variation to include rich sets of fixed effects, allowing us to examine how outside options shape the probabilities of job separation, industry exit and reemployment. With this analysis, we contribute to a growing literature studying the determinants of advisor misconduct (Egan et al., 2019; Dimmock et al., 2021; Clifford and Gerken, 2021).

We first scrutinize how variation in outside options influences the frequency of advisor misconduct, building on Equation (15). We aggregate inflows at ties to annual frequency by taking averages and focus on the first lag of the measure, as misconduct typically takes time to be discovered and disclosed. Our analysis considers three outcomes, namely the number of misconduct disclosures an advisor receives in a given year, the number of customer complaints filed against the advisor and the number of complaints that result in a settlement. Given the within-firm spillovers in misconduct (Egan et al., 2019), we control for the first lag of the firm-level average of the outcome variable. The results are shown in Table 13.

Better outside options correspond to statistically significant increases in misconduct disclosures, customer complaints and settled complaints under both the baseline specification and a specification with advisor-firm fixed effects. Across the six columns, a standard-deviation improvement in outside options raises the respective outcome by 2.1 to 3.6% of its standard deviation. The coefficients remain positive across robustness checks that add state-year fixed effects, use alternative timing assumptions, control for lagged outflows and use binary outcomes (Tables A26, A27 and A28). The associated costs to the financial sector are substantial. With average settlement costs of 550,000 USD per case (Egan et al., 2019), a standard-deviation increase in inflows at ties corresponds to an annual increase in settlement costs of approximately 140 million USD for the firms in our sample.

Egan et al. (2019) show that employment separations become more likely following advisor misconduct, while rehiring elsewhere partly offsets this penalty. Our mechanism posits that outside options reduce both the probability and the expected cost of separation for the employee, weakening the deterrent effect of job loss. We test this prediction using three transition outcomes and two empirical specifications. Specifically, for an advisor a employed at bank i in year t, we define three indicators for transitions between year t and $t+1$. The first is Separation_{at}, which equals one if the advisor is no longer employed at i. The second is IndustryExit_{at}, which equals one if the advisor is no longer recorded in the sample and thus exits the industry under our definition. The third is Reemployment_{at}, which equals one if the advisor is employed at another firm in the sample. We use two empirical specifications. First, we estimate the unconditional effects of misconduct, outside options and their interaction on Separation_{at} and IndustryExit_{at}.

Table 13: Effect of Outside Options on Misconduct Disclosures

	Misconduct		Complaints		Complaints (Settled)	
	(1)	(2)	(3)	(4)	(5)	(6)
IAT_{t-1}	0.003***	0.003***	0.005***	0.006***	0.004***	0.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lender fixed effects	X		X		X	
Year fixed effects	X	X	X	X	X	X
Lender × Adviser fixed effects		X		X		X
Lender Controls	X	X	X	X	X	X
Observations	582,568	551,079	582,568	551,079	582,568	551,079

Notes: The table reports results from estimating Equation (15) at annual frequency at the advisor level. The dependent variables are the number of misconduct disclosures an advisor had in a given year (Columns 1 and 2), the number of complaints filed against the advisor (Columns 3 and 4) and the number of settled customer complaints (Columns 5 and 6). The main independent variable is $InflowsAtTies_{it-1}$. Lender controls are the inverse hyperbolic sine transformations of total assets, net income, number of employees, EBIT, capital expenditure, total liabilities, short- and long-term debt and equity, together with the first lag of the firm-level average of the outcome variable. All models include lender controls and year fixed effects. Columns (1), (3) and (5) include lender fixed effects, while Columns (2), (4) and (6) replace them with lender-advisor fixed effects. Standard errors are two-way clustered by lender and calendar year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

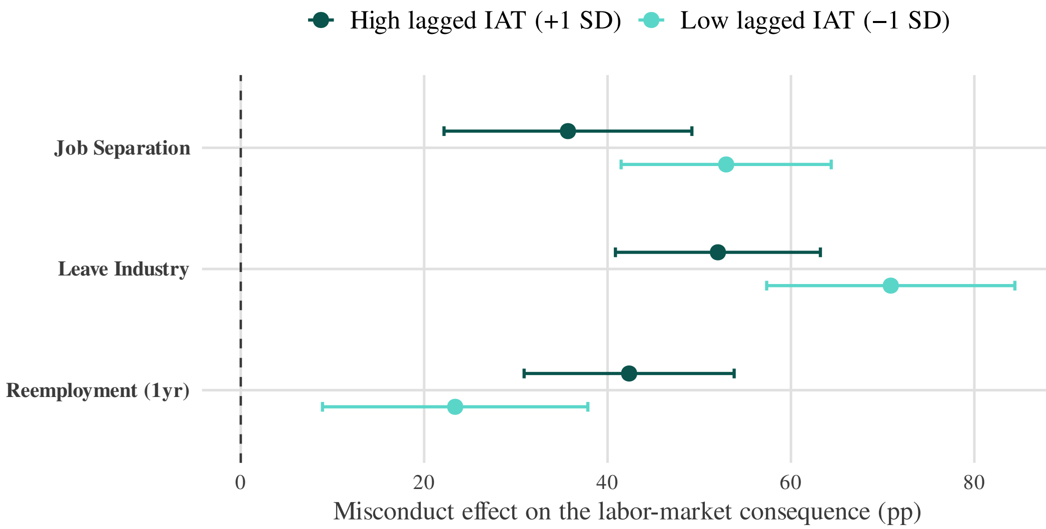
Second, we estimate how outside options alter the additional effect of job separation associated with misconduct on subsequent IndustryExit_{at} and Reemployment_{at}.

For the unconditional effects, the empirical specification is given by:

$$y_{at} = \beta_1 Misconduct_{at} + \beta_2 Misconduct_{at} \times InflowsAtTies_{it} + \beta_3 Misconduct_{at} \times InflowsAtTies_{it-1} + \alpha_{a,i} + \lambda_{it} + \epsilon_{ait}, \qquad (17)$$

that is, we regress an outcome y_{at} on an indicator for misconduct and its interaction with contemporaneous values and the first lag of inflows at ties. We include firm-year fixed effects, which absorb the standalone coefficient of outside options, and advisor or firm-advisor fixed effects. For the conditional effects, we further augment this setup by including all potential interactions with Separation_{at}, focusing on IndustryExit_{at} and Reemployment_{at} as outcome variables. The Separation × Misconduct coefficient and its

Figure 5: Advisor Misconduct and Labor Market Consequences by Outside Options



Notes: The figure uses annual observations at the advisor level. Low and high lagged outside options set lagged inflows at ties to one standard deviation below or above its mean, while contemporaneous inflows at ties remain at their mean. The job separation estimates report the marginal effect of a misconduct disclosure by lagged IAT level. The industry exit and reemployment estimates report the total marginal effect of job separation among advisors with misconduct. These total effects combine the main Separation and Separation × Misconduct terms with the Separation × lagged IAT term and the corresponding triple interaction. The regressions include firm-advisor and firm-year fixed effects and the full set of component terms. Marginal effects are reported in percentage points. Whiskers show 95% confidence intervals based on standard errors two-way clustered by firm and calendar year. Appendix Table A29 reports the full regression estimates.

interactions with IAT identify the increment specific to misconduct in the effect of separation.

Figure 5 summarizes the estimates from the specification with firm-advisor and firm-year fixed effects. Appendix Table A29 reports the full regression results. Holding contemporaneous IAT at its mean and increasing lagged IAT from its mean by one standard deviation, misconduct raises the probability of job separation by 44.3 percentage points at mean IAT and by 35.7 percentage points under higher lagged IAT. The reduction of 8.6 percentage points, or 19%, is statistically significant at the 5% level under two-way clustering by firm and calendar year. Better outside options therefore reduce the separation probability following a misconduct disclosure, providing evidence of reduced dismissal strictness by employers. The remaining outcomes separate the exit and hiring margins.

For the coefficient-based magnitudes, we hold contemporaneous IAT at its mean and increase lagged IAT from its mean by one standard deviation. At mean IAT, misconduct adds 12.7 percentage points to the industry-exit effect of separation. Higher lagged IAT reduces this penalty to 6.6 percentage points, an offset of 48% that is statistically significant at the 5% level. Misconduct also reduces the reemployment effect of separation by 12.7 percentage points at mean IAT. Higher lagged IAT reduces this penalty to 5.4 percentage points in absolute value, an offset of 57% that is statistically significant at the 1% level.

Taken together, these results suggest that outside options reduce the probability of separation following misconduct and, conditional on separation, predict continued employment within the sector. This pattern is consistent with diluted labor market discipline when outside options improve.

7 Conclusion

This paper shows that outside options make workplace discipline contingent on the state of the external labor market. When hiring at connected institutions strengthens, banks expand non-investment-grade lending and loans shift toward borrowers with greater ex-ante and realized risk, contributing to faster growth of bank and financial-sector tail risk. Evidence from individual bankers links these dynamics to career outcomes as outside options weaken the career penalty following poor loan performance. We identify a similar pattern of more misconduct and weaker employment penalties in a sample of financial advisors. Together, the results identify a discipline dilution channel that transmits labor market fluctuations into credit risk.

For policymakers, our findings suggest that labor market conditions may provide useful information for macroprudential supervision alongside traditional measures of bank leverage. An appropriate policy response is not immediately clear. Restrictions on mobility shut down the dilution channel in our sample but also severely restrict efficient worker-firm matching. Instead, regulators might aid monitoring efforts by collecting and publishing standardized measures of hiring and mobility. Firms that are less active in talent recruitment but still face an erosion of internal discipline could particularly benefit from such information.

References

Acharya, Viral, Marco Pagano, and Paolo Volpin (2016) "Seeking Alpha: Excess Risk Taking and Competition for Managerial Talent," *Review of Financial Studies*, 29 (10), 2565–2599.

Adrian, Tobias and Markus K. Brunnermeier (2016) "CoVaR," *American Economic Review*, 106 (7), 1705–1741.

Agarwal, Sumit, Yupeng Lin, Yunqi Zhang, and Zilong Zhang (2024) "Labor Mobility and Loan Origination," *Journal of Financial and Quantitative Analysis*, 59 (5), 2099–2132.

Ahammer, Alexander, Matthias Fahn, and Flora Stiftinger (2023) "Outside Options and Worker Motivation," Working Paper, JKU Linz.

Axelson, Ulf and Philip Bond (2015) "Wall Street Occupations," *Journal of Finance*, 70 (5), 1949–1996.

Azzopardi, Damien, Fozan Fareed, Mikkel Hermansen, Patrick Lenain, and Douglas Sutherland (2020) "The Decline in Labour Mobility in the United States: Insights from New Administrative Data," Working Papers, 1644, OECD Economics Department.

Behr, Patrick, Alejandro Drexler, Reint Gropp, and Andre Guettler (2020) "Financial Incentives and Loan Officer Behavior: Multitasking and Allocation of Effort Under an Incomplete Contract," *Journal of Financial and Quantitative Analysis*, 55 (4), 1243–1267.

Bell, Brian and John Van Reenen (2014) "Bankers and Their Bonuses," *Economic Journal*, 124 (574), F1–F21.

Berrospide, Jose M. and Rochelle M. Edge (2024) "Bank Capital Buffers and Lending, Firm Financing and Spending: What Can We Learn from Five Years of Stress Test Results?" *Journal of Financial Intermediation*, 57, 101061.

Böhm, Michael J, Daniel Metzger, and Per Strömberg (2023) ""Since You're So Rich, You Must Be Really Smart": Talent, Rent Sharing, and the Finance Wage Premium," *Review of Economic Studies*, 90 (5), 2215–2260.

Bonelli, Maxime (2019) "Labor Mobility and Capital Misallocation in the Mutual Fund Industry," Working Paper, University of Rochester.

Bordalo, Pedro, Nicola Gennaioli, Rafael La Porta, and Andrei Shleifer (2024) "Belief Overreaction and Stock Market Puzzles," *Journal of Political Economy*, 132 (5), 1450–1484.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel (2022) "Quasi-Experimental Shift-Share Research Designs," *Review of Economic Studies*, 89 (1), 181–213.

——— (2025) "A Practical Guide to Shift-Share Instruments," *Journal of Economic Perspectives*, 39 (1), 181–204.

Boxtel, Anton Van (2017) "Trader Compensation, Risk, and the Banking Labour Market," Working Paper, Institute for Advanced Studies Vienna.

Bramoullé, Yann and Gilles Saint-Paul (2010) "Social Networks and Labor Market Transitions," *Labour Economics*, 17 (1), 188–195.

Burdett, Kenneth and Dale T Mortensen (1998) "Wage Differentials, Employer Size, and Unemployment," *International Economic Review*, 257–273.

Bushman, Robert, Janet Gao, Xiumin Martin, and Joseph Pacelli (2021a) "The Influence of Loan Officers on Loan Contract Design and Performance," *Journal of Accounting and Economics*, 71 (2-3), 101384.

——— (2021b) "The Influence of Loan Officers on Loan Contract Design and Performance," *Journal of Accounting and Economics*, 71 (2-3), 101384.

Caldwell, Sydnee and Oren Danieli (2024) "Outside Options in the Labour Market," *Review of Economic Studies*.

Caldwell, Sydnee, Ingrid Haegele, and Jörg Heining (2025) "Firm Pay and Worker Search," Working Paper, 33445, National Bureau of Economic Research.

Caldwell, Sydnee, Ingrid Haegele, and Jörg Heining (2024) "Bargaining and Inequality in the Labor Market."

Caldwell, Sydnee and Nikolaj Harmon (2019) "Outside Options, Bargaining, and Wages: Evidence from Coworker Networks," Working Paper, Copenhagen University.

Carvalho, Daniel, Janet Gao, and Pengfei Ma (2023) "Loan Spreads and Credit Cycles: The Role of Lenders' Personal Economic Experiences," *Journal of Financial Economics*, 148 (2), 118–149.

Chava, Sudheer and Michael R Roberts (2008) "How Does Financing Impact Investment? The Role of Debt Covenants," *Journal of Finance*, 63 (5), 2085–2121.

Cici, Gjergji, Mario Hendriock, and Alexander Kempf (2021) "The Impact of Labor Mobility Restrictions on Managerial Actions: Evidence from the Mutual Fund Industry," *Journal of Banking & Finance*, 122, 105994, Publisher: Elsevier.

Cingano, Federico and Alfonso Rosolia (2012) "People I Know: Job Search and Social Networks," *Journal of Labor Economics*, 30 (2), 291–332.

Clifford, Christopher P and William C Gerken (2021) "Property Rights to Client Relationships and Financial Advisor Incentives," *Journal of Finance*, 76 (5), 2409–2445.

Dimmock, Stephen G, William C Gerken, and Tyson Van Alfen (2021) "Real Estate Shocks and Financial Advisor Misconduct," *Journal of Finance*, 76 (6), 3309–3346.

Dustmann, Christian, Albrecht Glitz, Uta Schönberg, and Herbert Brücker (2016) "Referral-Based Job Search Networks," *Review of Economic Studies*, 83 (2), 514–546.

Edmans, Alex, Xavier Gabaix, and Dirk Jenter (2017) "Executive Compensation: A Survey of Theory and Evidence," *Handbook of the Economics of Corporate Governance*, 1, 383–539.

Ee, Mong Shan and He Huang (2024) "Employee Mobility Constraints and Debt Choice," *Economics Letters*, 234, 111467.

Ee, Mong Shan, He Huang, and Mingying Cheng (2023) "Do Labor Mobility Restrictions Affect Debt Maturity?" *Journal of Financial Stability*, 66, 101121.

Egan, Mark, Gregor Matvos, and Amit Seru (2019) "The Market for Financial Adviser Misconduct," *Journal of Political Economy*, 127 (1), 233–295.

——— (2022) "When Harry Fired Sally: The Double Standard in Punishing Misconduct," *Journal of Political Economy*, 130 (5), 1184–1248.

——— (2024) "The Problem of Good Conduct Among Financial Advisers," *Journal of Economic Perspectives*, 38 (4), 193–210.

Ellul, Andrew, Marco Pagano, and Annalisa Scognamiglio (2020) "Career Risk and Market Discipline in Asset Management," *Review of Financial Studies*, 33 (2), 783–828.

Figueiredo, Ana (2022) "Wage Cyclicality and Labor Market Sorting," *American Economic Review: Insights*, 4 (4), 425–442.

Fracassi, Cesare, Stefan Petry, and Geoffrey Tate (2016) "Does Rating Analyst Subjectivity Affect Corporate Debt Pricing?" *Journal of Financial Economics*, 120 (3), 514–538.

Gao, Janet, Kristoph Kleiner, and Joseph Pacelli (2020) "Credit and Punishment: Are Corporate Bankers Disciplined for Risk-Taking?" *Review of Financial Studies*, 33 (12), 5706–5749.

Gao, Janet, Wenyu Wang, and Yufeng Wu (2024a) "Human Capital Mobility and Careers of M&A Advisors," *Review of Financial Studies*, 37 (9), 2732–2778.

Gao, Janet, Wenyu Wang, and Xiaoyun Yu (2024b) "Big Fish in Small Ponds: Human Capital Migration and the Rise of Boutique Banks," *Management Science*, 70 (11), 7345–8215.

Gee, Laura K, Jason Jones, and Moira Burke (2017) "Social Networks and Labor Markets: How Strong Ties Relate to Job Finding on Facebook's Social Network," *Journal of Labor Economics*, 35 (2), 485–518.

Glitz, Albrecht (2017) "Coworker Networks in the Labour Market," *Labour Economics*, 44, 218–230.

Godechot, Olivier (2014) "Getting a Job in Finance: The Strength of Collaboration Ties," *European Journal of Sociology/Archives EuropéEnnes De Sociologie*, 55 (1), 25–56.

Griffin, John M, Samuel Kruger, and Gonzalo Maturana (2019) "Do Labor Markets Discipline? Evidence from RMBS Bankers," *Journal of Financial Economics*, 133 (3), 726–750.

Guren, Adam M, Alisdair McKay, Emi Nakamura, and Jón Steinsson (2021) "Housing Wealth Effects: The Long View," *Review of Economic Studies*, 88 (2), 669–707.

Hamdi, Naser, Ankit Kalda, and Avantika Pal (2023) "External Labor Market Punishment in Finance," Working Paper, Indiana University.

Heider, Florian and Roman Inderst (2012) "Loan Prospecting," *Review of Financial Studies*, 25 (8), 2381–2415.

Hensvik, Lena and Oskar Nordström Skans (2016) "Social Networks, Employee Selection, and Labor Market Outcomes," *Journal of Labor Economics*, 34 (4), 825–867.

Herpfer, Christoph (2021) "The Role of Bankers in the US Syndicated Loan Market," *Journal of Accounting and Economics*, 71 (2-3), 101383.

Hertzberg, Andrew, Jose Maria Liberti, and Daniel Paravisini (2010) "Information and Incentives Inside the Firm: Evidence from Loan Officer Rotation," *Journal of Finance*, 65 (3), 795–828.

Hoffmann, Florian, Roman Inderst, and Marcus Opp (2022) "The Economics of Deferral and Clawback Requirements," *Journal of Finance*, 77 (4), 2423–2470.

Holmström, Bengt (1979) "Moral Hazard and Observability," *Bell Journal of Economics*, 74–91.

Huang, Ruidi, James S Linck, Erik J Mayer, and Chris Parsons (2024) "Can Human Capital Explain Income-Based Disparities in Financial Services," *Review of Financial Studies*, 22–16.

Huang, Ruidi, Erik J Mayer, Sheridan Titman, and David X Xu (2025) "Human Capital and Local Credit Supply: Evidence from the Mortgage Industry," SMU Cox School of Business, Working Paper.

Jäger, Simon, Christopher Roth, Nina Roussille, and Benjamin Schoefer (2024) "Worker Beliefs About Outside Options," *Quarterly Journal of Economics*, 139 (3), 1505–1556.

Jiang, John, Isabel Y Wang, and K Philip Wang (2018) "Revolving Rating Analysts and Ratings of Mortgage-Backed and Asset-Backed Securities: Evidence from LinkedIn," *Management Science*, 64 (12), 5832–5854.

Jiménez, Gabriel, Steven Ongena, José-Luis Peydró, and Jesús Saurina (2014) "Hazardous Times for Monetary Policy: What Do Twenty-Three Million Bank Loans Say About the Effects of Monetary Policy on Credit Risk-Taking?" *Econometrica*, 82 (2), 463–505.

Johnson, Matthew S, Kurt Lavetti, and Michael Lipsitz (2025) "The Labor Market Effects of Legal Restrictions on Worker Mobility," *Journal of Political Economy*, 133 (9), 2735–2793.

Jordà, Òscar, Moritz Schularick, and Alan M. Taylor (2013) "When Credit Bites Back," *Journal of Money, Credit and Banking*, 45 (s2), 3–28.

Jovanovic, Boyan (1979) "Job Matching and the Theory of Turnover," *Journal of Political Economy*, 87 (5, Part 1), 972–990.

McNamara, Yvonne and Damien P McLoughlin (2009) "Corporate Alumni Networks and Knowledge Flows," Working Paper, University College Dublin.

Montgomery, James D (1991) "Social Networks and Labor-Market Outcomes: Toward an Economic Analysis," *American Economic Review*, 81 (5), 1408–1418.

Mortensen, Dale T and Christopher A Pissarides (1999) "New Developments in Models of Search in the Labor Market," *Handbook of Labor Economics*, 3, 2567–2627.

Mueller, Clemens (2026) "Non-Compete Agreements and Labor Allocation Across Product Markets," *Review of Finance*, 30 (4), 1295–1329, 10.1093/rof/rfag006.

Mugasha, Agasha (2004) "The Secondary Market for Syndicated Loans: Loan Trading, Credit Derivatives, and Collateralized Debt Obligations," *Banking and Finance Law Review*, 19 (2), 199–236.

Myerson, Roger B (2012) "A Model of Moral-Hazard Credit Cycles," *Journal of Political Economy*, 120 (5), 847–878.

——— (2014) "Moral-Hazard Credit Cycles with Risk-Averse Agents," *Journal of Economic Theory*, 153, 74–102.

Nakamura, Alice, Emi Nakamura, Kyle Phong, and Jón Steinsson (2019) "New Evidence on the Cyclicality of Employer-To-Employer Flows from Canada," in *AEA Papers and Proceedings*, 109, 456–460.

Norden, Lars, Bernardus Van Doornik, and Weichao Wang (2025) "Labor Turnover, Information Production, and Bank Risk," Banco Central do Brasil, Working Paper, 626.

Philippon, Thomas and Ariell Reshef (2012) "Wages and Human Capital in the US Finance Industry: 1909–2006," *Quarterly Journal of Economics*, 127 (4), 1551–1609.

Ruggles, Steven, Sarah Flood, Matthew Sobek et al. (2025) "IPUMS USA: Version 16.0," [dataset].

Saygin, Perihan Ozge, Andrea Weber, and Michele A Weynandt (2021) "Coworkers, Networks, and Job-Search Outcomes Among Displaced Workers," *ILR Review*, 74 (1), 95–130.

Schubert, Gregor, Anna Stansbury, and Bledi Taska (2022) "Employer Concentration and Outside Options," 12, Working Paper, UCLA.

Schularick, Moritz and Alan M Taylor (2012) "Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870–2008," *American Economic Review*, 102 (2), 1029–1061.

Schwert, Michael (2020) "Does Borrowing from Banks Cost More Than Borrowing from the Market?" *Journal of Finance*, 75 (2), 905–947.

Shue, Kelly (2013) "Executive Networks and Firm Policies: Evidence from the Random Assignment of MBA Peers," *Review of Financial Studies*, 26 (6), 1401–1442.

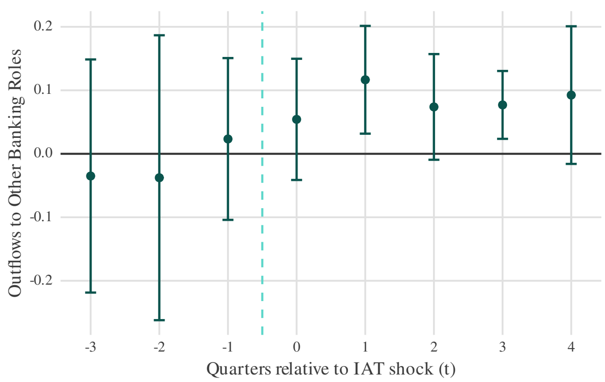
SIFMA (2019) "US Quarterly Highlights - 2018 Q4," `https://www.sifma.org/wp-content/uploads/2019/01/US-Quarterly-Highlights-2018Q4-2019-01-11-SIFMA.pdf`, Accessed: 2024-11-04.

Thanassoulis, John (2012) "The Case for Intervening in Bankers' Pay," *Journal of Finance*, 67 (3), 849–895.

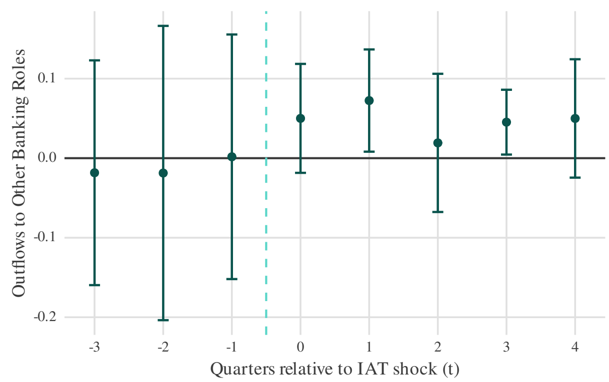
A Additional Figures

Figure A1: Effect of Outside Options on Outflows, Robustness to Alternative Tie Lengths

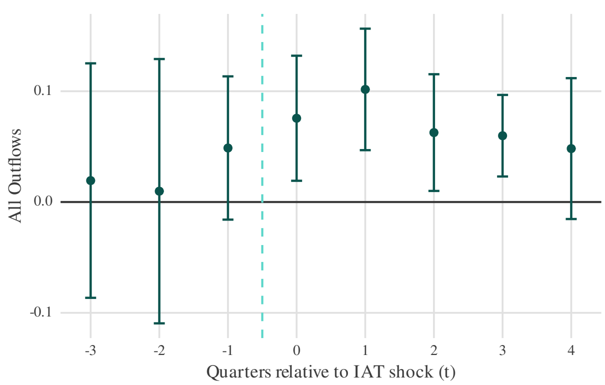
(a) Banking Roles, Ties Active 2–12 Quarters



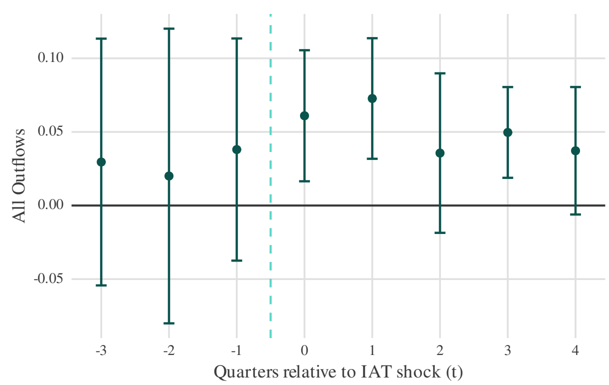
(b) Banking Roles, Ties Active 4–20 Quarters



(c) All Roles, Ties Active 2–12 Quarters

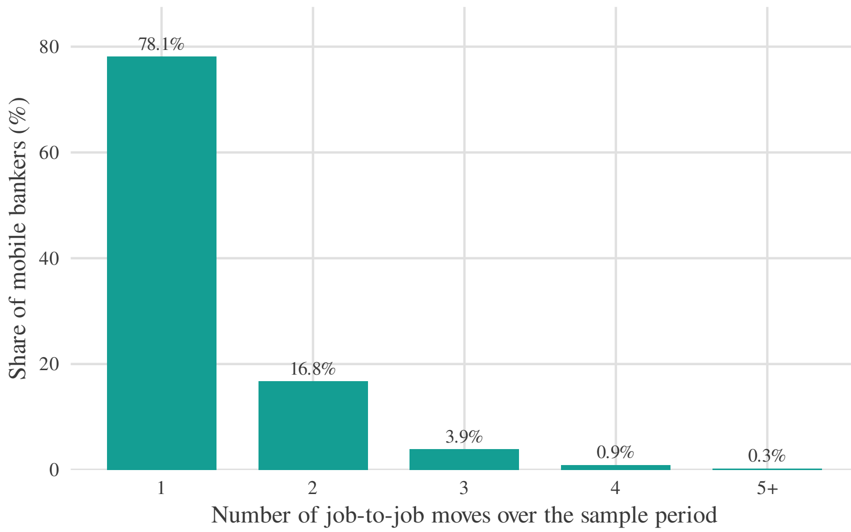


(d) All Roles, Ties Active 4–20 Quarters



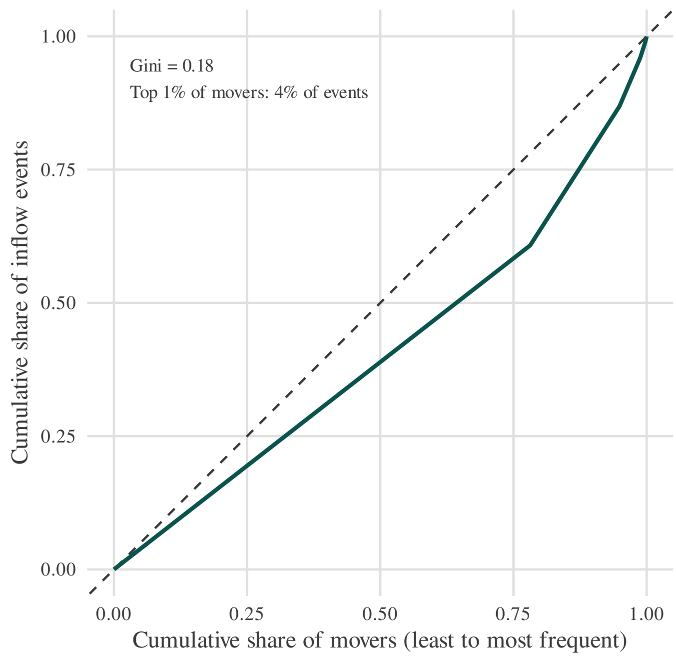
Notes: Points show coefficients from separate Poisson regressions of employee outflows on inflows at ties at horizons from three quarters before through four quarters after the shock. Panels a and c use ties active 2 to 12 quarters after a coworker transition, while Panels b and d use ties active 4 to 20 quarters after a transition. Whiskers show 95% confidence intervals based on two-way clustered standard errors at the lender and year-quarter levels. All regressions include lender and year-quarter fixed effects. Inflows at ties are standardized to have mean zero and standard deviation one.

Figure A2: Job-to-Job Moves per Mobile Banker



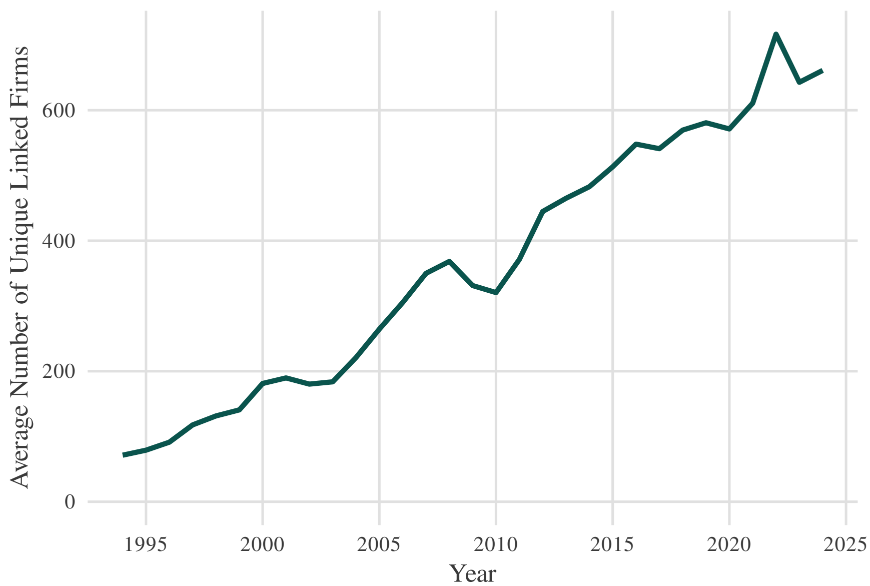
Notes: The figure shows the distribution of the number of job-to-job transitions per banker among senior U.S. bankers who make at least one such move over the sample period. The sample is the full sample and is not restricted to the matched estimation sample. A job-to-job move occurs when a banker changes ultimate parent employer and the new spell starts no more than 31 days after the preceding spell ends. The average across mobile bankers of each banker's mean observed job spell length is 4.8 years. Moves of five or more are grouped.

Figure A3: Concentration of Inflow Events Across Movers



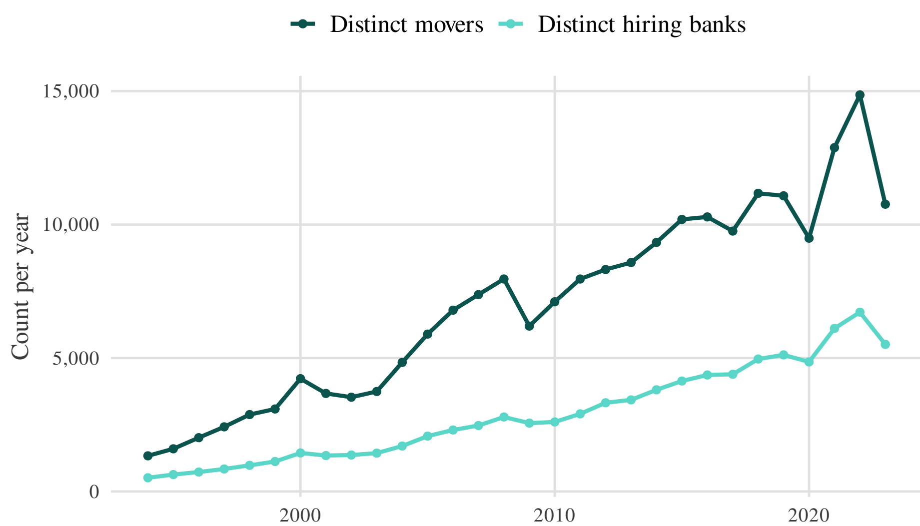
Notes: The figure plots the Lorenz curve of job-to-job inflow events across movers, ranked from least to most frequently mobile (full sample). The dashed line is the line of equality.

Figure A4: Number of Connected Banks over Time



Notes: The figure plots the annual average of quarterly counts of connected hiring banks. For each quarter, the count includes a connected bank only when it has a positive active tie share and positive job-to-job hiring and when the focal bank belongs to the main estimation sample. Job-to-job hires are moves with an employment gap of one month or less. The quarterly counts are first constructed from the inflows-at-ties panel and are then averaged within calendar years.

Figure A5: Number of Distinct Movers and Hiring Banks



Notes: The figure plots, per year, the number of distinct senior bankers making job-to-job moves into connected banks and the number of distinct hiring (connected) banks that generate the inflow shocks (full sample).

B Additional Tables

Table A1: Summary Statistics: Loan Level Data

Variable	N	Mean	SD	P25	P50	P75
Panel A. Dealscan Loan-Level Data						
Borrower Prime	55327	0.3	0.46	0	0	1
Borrower Rating	55327	0.46	0.2	0.25	0.5	0.62
Tranche Amount	55327	905	1623	150	400	1000
Maturity	55327	50	23	36	58	60
Secured	55327	0.51	0.5	0	1	1
Covenants	55327	0.48	0.5	0	0	1
Panel B. FISD Borrower Ratings						
Below-Investment-Grade Borrower	30,146	0.56	0.50	0.00	1.00	1.00
Borrower Risk Score, 0–100	30,146	50.35	18.25	38.10	47.62	66.67
Median FISD Rating, 1–22	30,146	11.43	3.83	8.00	12.00	14.00
Active Bond–Agency Ratings	30,146	28.82	53.42	4.00	12.00	33.00

Notes: Panel A reports loan-tranche-level summary statistics for the Dealscan sample. *Borrower Prime* indicates an investment-grade borrower, *Borrower Rating* is an ordinal S&P issuer-level rating normalized to the unit interval, tranche amount is in millions of USD and maturity is in months. Panel B reports statistics for the subsample with a contemporaneous Mergent FISD issue-level rating. For each tranche, the most recent rating in effect on or before origination is retained for every active bond–agency pair and the median is taken across S&P, Moody's and Fitch ratings. Ratings map to a 22-point scale from D to AAA/Aaa. The borrower risk score maps this rating to a 0–100 scale, with higher values indicating greater risk. The sample spans 1994 to 2020.

Table A2: Summary Statistics: Employment History Data

	N	Mean	Weighted Mean	SD	P25	P50	P75
Male	801049	0.69	0.68	0.46	0.00	1.00	1.00
White	802908	0.78	0.78	0.42	1.00	1.00	1.00
Bachelor	634528	0.50	0.50	0.50	0.00	1.00	1.00
More than Bachelor	634528	0.48	0.48	0.50	0.00	0.00	1.00
Salary (in 1000)	803076	150.06	149.55	69.22	102.56	135.27	181.38
Age at Start	771951	33.55	33.53	8.18	28.20	32.60	38.40
Age at Middle	771951	36.69	36.66	8.28	30.85	35.68	41.71
Age at End	771951	39.83	39.80	9.69	32.91	38.31	45.36
Seniority	803096	4.75	4.75	0.74	4.00	5.00	5.00
Nr. of Previous Positions	803096	3.02	3.03	2.62	1.00	3.00	4.00

Notes: The table reports spell-level summary statistics on demographic variables for the sample of senior employees working in credit origination described in Section 3. The full sample in Panel A includes all employment spells reported in the United States, in the respective job roles and at seniority level 4 or above. *Male*, *White*, *Bachelor* and *More Than Bachelor* are indicator variables equal to one for the corresponding categories. *Salary* is an imputed variable based on observable characteristics of an employment spell and measured in thousands of USD. The age variables refer to the beginning, middle and end of an employment spell. *Seniority* is the seniority ranking, with values between 4 (lowest) and 7 (highest). *Nr. of Previous Positions* counts the number of positions held before the current spell. Panel B reports demographic summary statistics for the sample of bankers matched to individual loans at the loan-signature date. *Age* and *Job Tenure* are measured in years. *Seniority* is the seniority ranking, with values between 0 (lowest) and 7 (highest). *Salary* is an imputed variable based on observable characteristics of an employment spell and measured in thousands of USD. *Weighted Mean* uses sampling weights constructed by Revelio Labs (see here for details).

Table A3: Summary Statistics: Employment History Data vs. Survey Data

	Estimation Sample	Full Sample	CPS	ACS
Male	0.68	0.63	0.57	0.57
White	0.78	0.74	0.84	0.82
Bachelor	0.50	0.56	0.49	0.46
More than Bachelor	0.48	0.40	0.17	0.17
Salary (in 1000)	149.55	102.10	98.31	100.91
Age	36.66	32.15	40.84	40.13
Observations (in 1000)	607.60	1657.54	20.23	304.14

Notes: The table reports spell-level weighted averages of demographic variables, comparing the employment-biography data with demographic sources. *Estimation Sample* includes all employment spells reported in the United States, in the respective job roles and at seniority level 4 or above, as described in Section 3. *Full Sample* relaxes the latter restriction and includes all seniority levels in the employment-spell data. *CPS* and *ACS* use survey data from the *Current Population Survey* and the *American Community Survey*, respectively. For the CPS and ACS, we retain all observations between 1994 and 2023 for individuals who are in the labor force, are at work and employed full time, are younger than 66 and have hourly income of at least USD 10, equivalent to USD 21,600 annually. We restrict the sample to employment in the financial industry, using 1990 industry classification codes from 700 to 710 and occupations related to loan origination, using 2010 occupation codes 0120, 0830, 0840, 0850, 0910 and 4820. *Male*, *White*, *Bachelor* and *More Than Bachelor* are indicator variables equal to one for the corresponding categories. *Salary* is measured in thousands of USD. For the employment-history data, it is an imputed measure based on observable characteristics of an employment spell. *Age* is age at the midpoint of an employment spell for the spell-level data. *Observations* is the number of observations that are nonmissing for all listed variables.

Table A4: Summary Statistics: Borrower- and Lender-level Outcomes and Controls

	N	Mean	SD	P25	P50	P75
Panel A: Borrower Characteristics						
Total Assets	55,327	29,702.32	126,413.95	1,906.80	6,370.07	18,754.20
Capex	55,327	929.33	2,594.73	32.23	138.41	597.25
Employees	55,327	31.12	96.96	2.33	8.41	25.70
Liabilities	55,327	23,160.37	111,742.11	1,200.10	4,217.55	13,194.50
EBIT	55,327	1,308.43	3,782.17	79.63	349.00	1,097.00
Net Income	55,327	608.39	2,833.28	-1.61	111.60	507.10
Current Debt	55,327	2,651.48	19,409.86	10.00	74.20	503.00
Long Term Debt	55,327	8,157.54	21,938.02	568.89	2,077.75	6,840.00
Stockholder Equity	55,327	6,162.13	17,864.16	381.04	1,500.63	4,700.43
Book Leverage (Debt/Assets, in Ppt.)	55,327	40.73	22.33	25.33	38.59	53.56
Panel B: Lender Characteristics						
Total Assets	55,327	1,325,920.98	809,725.31	687,935.00	1,198,942.00	1,930,115.00
Capex	55,327	1,411.17	2,171.85	73.00	934.11	1,497.20
Employees	55,327	112.34	81.66	51.20	80.00	163.50
Liabilities	55,327	1,235,089.55	761,271.58	645,607.00	1,108,646.00	1,757,212.00
EBIT	55,327	20,601.01	14,427.06	10,750.51	17,104.00	26,337.57
Net Income	55,327	7,169.74	7,446.01	2,655.00	5,579.94	10,101.96
Current Debt	55,327	176,537.77	130,782.04	73,136.00	161,592.54	262,878.00
Long Term Debt	55,327	120,202.79	84,346.79	32,771.00	127,663.64	178,324.00
Stockholder Equity	55,327	88,314.10	62,474.38	44,354.00	75,397.31	110,450.56
Panel C: VAR and CoVaR						
VAR Level (95th Pctile)	26,501	0.067	0.036	0.044	0.058	0.081
CoVaR Level (95th Pctile)	26,501	0.009	0.007	0.004	0.008	0.013
VAR Level (99th Pctile)	26,501	0.114	0.060	0.073	0.098	0.140
CoVaR Level (99th Pctile)	26,501	0.013	0.010	0.007	0.012	0.018
VAR Growth (95th Pctile, pp)	26,734	-0.08	21.55	-10.87	-0.56	10.05
CoVaR Growth (95th Pctile, pp)	26,734	-0.07	19.55	-9.16	-0.44	8.36
VAR Growth (99th Pctile, pp)	26,734	-0.05	20.69	-10.12	-0.27	9.44
CoVaR Growth (99th Pctile, pp)	26,734	-0.04	19.69	-9.29	-0.17	8.50
Panel D: Lending Outcomes						
Total Loan Volume Growth (pp)	25,587	1.18	102.53	-25.20	0.00	32.36
IG Loan Volume Growth (pp)	25,587	1.44	100.66	-20.73	0.00	27.68
Non-IG Loan Volume Growth (pp)	25,587	0.57	75.24	0.00	0.00	0.00
Total Loan Volume ($m)	25,587	12,182.35	47,913.66	0.00	64.42	1,999.41
IG Loan Volume ($m)	25,587	10,012.29	37,722.93	0.00	45.00	1,830.24
Non-IG Loan Volume ($m)	25,587	2,170.06	11,762.34	0.00	0.00	0.00

Notes: This table reports summary statistics for borrower-firm controls in Panel A and lender-firm controls in Panel B. Variables come from the Compustat Fundamentals North America and Global databases. Accounting variables are measured in millions of USD, employee counts are measured in thousands and book leverage is transformed into percentage points. Panel C reports the levels and growth rates of Value at Risk and Conditional Value at Risk from Adrian and Brunnermeier (2016). Growth rates are transformed into percentage points. The data are quarterly and span 1994 to 2009. Panel D reports total, investment-grade and non-investment-grade lending volumes and their growth rates at the lender-quarter level for the outcomes used in Table 1. Loan volumes are measured in millions of USD and growth rates are midpoint rates transformed into percentage points.

Table A5: Summary Statistics: Compensation Data

	N	Mean	SD	P25	P50	P75
Median Salary (in $1000)	8,663	779.13	394.01	500.00	760.00	1,000.00
Median Bonus (in $1000)	8,663	583.41	1,738.23	0.00	0.00	603.50
Median Equity at Risk (in $1000)	8,527	9,140.57	19,685.08	2,309.75	5,610.50	11,094.50
Median Salary (Growth, in Ppt.)	8,668	3.56	27.25	0.00	2.59	9.89
Median Bonus (Growth, in Ppt.)	8,668	-4.29	85.55	0.00	0.00	2.03
Median Equity at Risk (Growth, in Ppt.)	8,668	2.42	75.40	-36.17	0.00	43.06

Notes: The table reports summary statistics for BoardEx compensation data. Salary, bonus and equity at risk are medians among senior non-executive bankers at the bank-year level and are measured in thousands of USD. Growth variables use midpoint rates transformed into percentage points. The sample spans 1997 to 2020.

Table A6: Summary Statistics: Outside Options Measure

Var	N	Mean	SD	P25	P50	P75
Nr. of Employees	19378	316.77	750.68	19.00	82.00	258.00
Nr. of Connected Bankers	19378	40.34	105.46	2.00	8.00	29.00
Nr. of Bank-Level Ties	19378	23.58	45.27	2.00	7.00	23.00
Nr. of Bank-Level Ties (Size-corrected)	19378	13.12	15.68	2.00	6.40	18.28
Nr. of Bank-Level Ties With Positive Inflows	19378	11.54	20.49	1.00	3.00	13.00
Average Job-to-Job Hiring at Ties	19378	6.67	9.26	1.56	4.40	8.12
Inflows At Ties	19378	6.55	9.28	1.00	4.00	8.83

Notes: This table shows summary statistics related to the outside options measure $InflowsAtTies$ by lender at the quarterly level. *Number of Employees* refers to the number of sampled individuals at the bank. *Number of Connected Bankers* is the number of individuals working in other institutions with active ties. *Number of bank-level Ties* is the number of distinct banks with active ties, reported equally weighted, size-corrected using the inverse Herfindahl index of Borusyak et al. (2025) and restricted to ties with positive inflows. *Average Job-to-Job Hiring at Ties* is the mean inflow at tied banks, conditional on hired individuals transitioning between jobs with a gap of one month or less. *Inflows at Ties* is the outside options proxy prior to normalization.

Table A7: Outside Options and Individual Worker Mobility

	Job-to-Job (1y, pp)	Job-to-Job (2y, pp)	Out of Finance (2y, pp)
	(1)	(2)	(3)
IAT	0.100**	0.250**	-0.010
	(0.050)	(0.110)	(0.060)
Seniority	-2.020***	-3.590***	-1.280***
	(0.090)	(0.180)	(0.090)
Employer FE	X	X	X
Year-Quarter FE	X	X	X
Observations	906,741	861,156	861,156

Notes: The table reports individual-level linear probability models. Each observation is one senior U.S.-finance spell. Outcomes are indicators for a job-to-job move within one year and two years and a move out of the finance sector within two years. Each dependent variable is multiplied by 100 before estimation, so coefficients are in percentage points. $InflowsAtTies_{it}$ is standardized to unit variance. All columns include bank and year-quarter fixed effects, as well as seniority controls. Standard errors are two-way clustered at the bank and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Effect of Outside Options on Pay Growth (in Percentage Points)

	Salary		Bonus		Equity At Risk	
	(1)	(2)	(3)	(4)	(5)	(6)
IAT	0.081***	0.078**	-0.177	-0.182	0.082	0.082
	(0.029)	(0.031)	(0.123)	(0.140)	(0.094)	(0.096)
Lender FE	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X
Lender Controls		X		X		X
Observations	8,462	8,462	8,462	8,462	8,462	8,462

Notes: The table shows regressions of midpoint growth rates of median firm-level compensation on $InflowsAtTies_{it}$, lender controls and fixed effects at the lender and year-quarter level. The dependent variables are salary (Columns 1 and 2), bonus payments (Columns 3 and 4) and equity at risk (Columns 5 and 6). Lender controls are the inverse hyperbolic sine transformations of total assets, net income, number of employees, EBIT, capital expenditure, total liabilities, short- and long-term debt and equity. Standard errors are two-way clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Outside Options and Bank-level Covariates in Levels

	IAT Lead 1Q (1)	IAT Lead 2Q (2)	IAT Lead 3Q (3)	IAT Lead 4Q (4)
Log Assets	-0.338	-0.313	-0.319	-0.333
	(0.337)	(0.332)	(0.336)	(0.345)
Log EBIT	0.005	0.005	0.012	0.028
	(0.040)	(0.036)	(0.034)	(0.034)
Log Current Liabilities	0.113*	0.072	0.052	0.049
	(0.062)	(0.074)	(0.084)	(0.088)
Log Long-Term Debt	-0.120	-0.144	-0.133	-0.131
	(0.175)	(0.178)	(0.175)	(0.173)
Log Liabilities	0.473	0.450	0.432	0.422
	(0.369)	(0.362)	(0.354)	(0.349)
Log Equity	0.019	0.014	0.027	0.023
	(0.077)	(0.076)	(0.076)	(0.072)
Log Capital Expenditures	-0.176	-0.124	-0.121	-0.112
	(0.112)	(0.127)	(0.131)	(0.140)
Log Net Income	-0.007	0.0007	0.001	0.003
	(0.029)	(0.028)	(0.024)	(0.024)
Lender FE	X	X	X	X
Year-Quarter FE	X	X	X	X
Observations	11,964	11,964	11,964	11,964

Notes: The table reports lender-quarter OLS regressions in which the dependent variable is $InflowsAtTies_{i,t+h}$ for horizons $h = 1,\ldots,4$, as indicated by the column headings. $InflowsAtTies$ is reported in its unstandardized units. The eight covariates enter each regression jointly. They are the inverse hyperbolic sine transformations of total assets, EBIT, current liabilities, long-term debt, total liabilities, stockholders' equity, capital expenditures and net income from Compustat. All columns include lender and year-quarter fixed effects. Standard errors that are two-way clustered at the lender and year-quarter levels are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Outside Options and Bank-level Covariates in Growth Rates

	IAT Lead 1Q (1)	IAT Lead 2Q (2)	IAT Lead 3Q (3)	IAT Lead 4Q (4)
Asset Growth	-0.217	0.206	0.201	0.180
	(0.610)	(0.668)	(0.652)	(0.654)
EBIT Growth	-0.008	0.002	0.022	0.038**
	(0.021)	(0.020)	(0.018)	(0.018)
Current Liabilities Growth	0.111*	0.076*	0.044	0.036
	(0.057)	(0.040)	(0.033)	(0.037)
Long-Term Debt Growth	0.008	0.006	-0.011	-0.018
	(0.226)	(0.230)	(0.215)	(0.198)
Liabilities Growth	0.170	-0.017	-0.047	0.024
	(0.527)	(0.476)	(0.448)	(0.421)
Equity Growth	0.009	0.004	0.018	0.021
	(0.044)	(0.043)	(0.048)	(0.043)
Capital Expenditures Growth	-0.025	0.124	0.129	0.145
	(0.155)	(0.101)	(0.112)	(0.144)
Net Income Growth	-0.016	-0.009	-0.008	-0.004
	(0.015)	(0.015)	(0.016)	(0.016)
Lender FE	X	X	X	X
Year-Quarter FE	X	X	X	X
Observations	11,268	11,268	11,268	11,268

Notes: The table reports lender-quarter OLS regressions in which the dependent variable is $InflowsAtTies_{i,t+h}$ for horizons $h = 1,\ldots,4$, as indicated by the column headings. $InflowsAtTies$ is reported in its unstandardized units. The eight covariates enter each regression jointly. Each growth measure is the first difference in the inverse hyperbolic sine of the corresponding annual Compustat variable between consecutive fiscal-year observations. The variables are total assets, EBIT, current liabilities, long-term debt, total liabilities, stockholders' equity, capital expenditures and net income. All columns include lender and year-quarter fixed effects. Standard errors that are two-way clustered at the lender and year-quarter levels are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: Concentration and Co-Movement of Hiring Shocks

Panel A. Variance of hiring at connected banks explained by (R^2):	
Common cycle (year-quarter)	0.024
Connected bank j	0.415
Connected bank j + year-quarter	0.447
Industry segment × year-quarter	0.052
Geographic region × year-quarter	0.060
Panel B. Intra-class correlation, net of the common cycle	
Connected bank j	0.425
Industry segment	0.016
Geographic region	0.018
Industry segment × year-quarter	0.029
Geographic region × year-quarter	0.037
Panel C. Dispersion of identifying variation	
Effective number of shocks $\left(1/\sum_n s_n^2\right)$	251.750
Largest exposure share ($\max_n s_n$)	0.027

Notes: The shock is job-to-job hiring at connected bank j in quarter t (inverse hyperbolic sine). Panel A reports the R^2 from regressing the shock on the indicated fixed effects. Panel B reports intra-class correlations after removing year-quarter means, i.e. the share of residual shock variance that lies between clusters, while the industry segment is the connected bank's three-digit NAICS sector and the region is its metropolitan area. Panel C reports the inverse Herfindahl of shock-level average exposure aggregated to the connected bank and the single largest such exposure share, over the estimation sample (gvkey-linked lenders, $t \geq 17$).

Table A12: Effect of Outside Options on Loan Volume, Separate Lending at Ties Controls

	Total		Non-Inv. Grade		Inv. Grade	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Total Syndicated Lending at Ties						
IAT	0.624	0.478	1.714***	3.450***	0.590	0.782
	(0.741)	(1.582)	(0.443)	(1.042)	(0.761)	(1.590)
Lending at ties, level	X	X	X	X	X	X
Lending at ties, annual growth	X	X	X	X	X	X
Panel B. Leveraged Lending at Ties, Spread Definition						
IAT	0.783	0.638	1.710***	3.408***	0.783	0.994
	(0.745)	(1.572)	(0.464)	(1.048)	(0.765)	(1.576)
Lending at ties, level	X	X	X	X	X	X
Lending at ties, annual growth	X	X	X	X	X	X
Panel C. Leveraged Lending at Ties, Rating Definition						
IAT	0.817	0.616	1.764***	3.445***	0.760	0.885
	(0.798)	(1.604)	(0.475)	(1.053)	(0.810)	(1.607)
Lending at ties, level	X	X	X	X	X	X
Lending at ties, annual growth	X	X	X	X	X	X
Panel D. Leveraged Lending at Ties, Loan Purpose Definition						
IAT	0.533	0.326	1.755***	3.388***	0.526	0.673
	(0.756)	(1.598)	(0.460)	(1.040)	(0.777)	(1.609)
Lending at ties, level	X	X	X	X	X	X
Lending at ties, annual growth	X	X	X	X	X	X
Lender FE	X		X		X	
Lender × Year FE		X		X		X
Year-Quarter FE	X	X	X	X	X	X
Observations	25,378	25,219	25,378	25,219	25,378	25,219

Notes: The table re-estimates the loan volume regressions of Table 1. Each panel jointly controls for the standardized exposure-weighted level and annual growth rate of one lending measure at connected banks. Panel A uses total syndicated lending. Panel B defines leveraged lending using spreads of at least 200 basis points. Panel C uses borrowers rated below investment grade. Panel D uses loan purposes associated with buyouts, mergers and acquisitions and recapitalizations. The dependent variables, fixed effects and sample follow Table 1. Standard errors are two-way clustered at the lender and year-quarter levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A13: Inflows at Borrowers and Transitions to Borrower Relationship Firms

	Number of transitions to ongoing borrower firms			
Outcome window	1 quarter	2 quarters	3 quarters	4 quarters
	(1)	(2)	(3)	(4)
Inflows at Borrowers	0.205**	0.248***	0.254***	0.273***
	(0.088)	(0.082)	(0.082)	(0.088)
Lender FE	X	X	X	X
Year-Quarter FE	X	X	X	X
Observations	2722	2722	2722	2722

Notes: The table reports lender-quarter quasi-Poisson regressions of the number of worker transitions from lender i to firms in its ongoing borrower relationship set measured in quarter t. The outcome covers quarter t in Column (1) to quarters t through $t+3$ in Column (4). Worker transitions are restricted to the senior finance roles. An ongoing lender-borrower relationship requires at least two loans whose maturity windows overlap or are separated by no more than 90 days. Relationship exposure begins four quarters after the second qualifying loan and remains active through eleven quarters after relationship maturity. Inflows at Borrowers combines shares based on these predetermined lender-borrower relationships with senior finance hiring at the borrower firms. Hires arriving from a given lender i are removed from the borrower hiring shift. IAB is standardized to unit variance on the common estimation sample. All four columns include lender and year-quarter fixed effects. Standard errors are two-way clustered by lender and year-quarter. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A14: Effect of Outside Options on Lending Volumes, Additional Robustness

	Total			Non-Inv. Grade			Inv. Grade		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. Origination-only lending									
IAT	0.528	0.772	1.503	1.891^{***}	4.261^{***}	2.056^{***}	0.388	0.675	1.549
	(0.720)	(1.599)	(1.084)	(0.449)	(0.984)	(0.772)	(0.713)	(1.558)	(0.974)
Observations	25,378	25,219	6,296	25,378	25,219	6,296	25,378	25,219	6,296
Panel B. Per-lead-share allocation									
IAT	-0.045	-0.778	0.505	1.348^{***}	2.470^{**}	1.103	-0.107	-0.299	0.571
	(0.576)	(1.337)	(0.790)	(0.474)	(1.199)	(0.912)	(0.629)	(1.358)	(0.890)
Observations	25,378	25,219	6,296	25,378	25,219	6,296	25,378	25,219	6,296
Panel C. Excluding the 2007–2008 financial crisis									
IAT	-0.229	-1.112	0.919	1.627^{***}	3.324^{**}	2.372^{**}	-0.287	-0.518	0.593
	(0.668)	(1.789)	(1.337)	(0.467)	(1.322)	(1.155)	(0.704)	(1.847)	(1.398)
Observations	23,300	23,147	5,666	23,300	23,147	5,666	23,300	23,147	5,666
Panel D. Adding Inflows at Co-Signatories									
IAT	0.616	1.457	0.763	1.554^{**}	2.509^{*}	2.086^{**}	0.967	1.520	0.791
	(1.401)	(1.416)	(1.486)	(0.709)	(1.286)	(0.839)	(1.513)	(1.581)	(1.532)
IAC	X	X	X	X	X	X	X	X	X
Observations	4,014	3,640	2,331	4,014	3,640	2,331	4,014	3,640	2,331
Lender FE	X		X	X		X	X		X
Lender × Year FE		X			X			X	
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Lender controls			X			X			X

Notes: Each panel re-estimates the lending volume regressions of Table 1. Within each outcome block, the first column includes lender and year-quarter fixed effects, the second includes lender-year and year-quarter fixed effects and the third adds time-varying lender controls. Panel A uses origination volume. Panel B allocates each facility amount equally across its lead arrangers. Panel C excludes 2007 and 2008. Panel D adds Inflows at Co-Signatories, IAC. $InflowsAtTies_{it}$ and IAC are standardized to unit variance. Standard errors are two-way clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A15: Outside Options and Lending Volumes by Seniority

	Growth Rate			Growth Rate (non-prime)			Growth Rate (prime)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. Original IAT									
IAT	0.395	1.230	1.620**	1.550***	2.810***	1.650**	0.344	1.540	1.640*
	(0.690)	(1.220)	(0.807)	(0.387)	(0.997)	(0.728)	(0.736)	(1.310)	(0.919)
Observations	25,378	25,199	6,296	25,378	25,199	6,296	25,378	25,199	6,296
Panel B. OO – medium seniority									
IAT	0.416	1.280	1.520*	1.540***	2.710***	1.470**	0.366	1.590	1.530*
	(0.711)	(1.170)	(0.791)	(0.399)	(1.020)	(0.675)	(0.762)	(1.270)	(0.911)
Observations	25,378	25,199	6,296	25,378	25,199	6,296	25,378	25,199	6,296
Panel C. OO – high seniority									
IAT	0.209	0.639	1.830**	1.300***	2.480***	2.340**	0.165	0.831	1.920**
	(0.599)	(1.320)	(0.888)	(0.424)	(0.921)	(1.000)	(0.609)	(1.350)	(0.937)
Observations	25,378	25,199	6,296	25,378	25,199	6,296	25,378	25,199	6,296
Lender FE	X		X	X		X	X		X
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Lender × Year FE		X			X			X	
Lender Controls			X			X			X

Notes: The table reports regressions of the midpoint growth rate of a bank's quarterly lead-arranged lending volume, transformed into percentage points, on standardized IAT. Each facility is credited to its lead arranger exactly once at its full amount. Columns (1)–(3) use total lending volume, Columns (4)–(6) use its non-investment-grade component and Columns (7)–(9) use its investment-grade component. Panel A uses the original IAT. Panel B recomputes IAT from job-to-job hires with seniority levels 4–5 and Panel C recomputes IAT from job-to-job hires with seniority levels 6–7. Within each panel, IAT is standardized in the estimation sample. Within each outcome block, the first column includes lender and year-quarter fixed effects, the second replaces lender fixed effects with saturated lender-year fixed effects and the third adds time-varying lender controls. Lender controls are the inverse hyperbolic sine transformations of total assets, net income, number of employees, EBIT, capital expenditure, total liabilities, short- and long-term debt and equity. The data span 1994 to 2020. Standard errors are two-way clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A16: Effect of Outside Options on Lending Volumes, Tie Length Robustness

	Growth Rate			Growth Rate (non-prime)			Growth Rate (prime)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. Baseline: ties active 4 to 12 quarters									
IAT	0.395	1.230	1.620**	1.550***	2.810***	1.650**	0.344	1.540	1.640*
	(0.690)	(1.220)	(0.807)	(0.387)	(0.997)	(0.728)	(0.736)	(1.310)	(0.919)
Observations	25,378	25,199	6,296	25,378	25,199	6,296	25,378	25,199	6,296
Panel B. Ties active 2 to 12 quarters									
IAT	0.354	0.659	1.470	1.470***	2.750***	1.990***	0.101	0.736	1.260
	(0.750)	(1.470)	(0.946)	(0.349)	(0.895)	(0.694)	(0.751)	(1.480)	(1.130)
Observations	25,378	25,199	6,296	25,378	25,199	6,296	25,378	25,199	6,296
Panel C. Ties active 4 to 20 quarters									
IAT	1.230**	2.340**	2.030**	1.230***	2.360***	1.940***	1.210*	2.670**	2.010**
	(0.598)	(1.090)	(0.774)	(0.346)	(0.848)	(0.449)	(0.631)	(1.160)	(0.897)
Observations	25,378	25,199	6,296	25,378	25,199	6,296	25,378	25,199	6,296
Lender FE	X		X	X		X	X		X
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Lender-year FE		X			X			X	
Lender Controls			X			X			X

Notes: The table reports results from regressing the outcome of interest on standardized $InflowsAtTies_{it}$ and fixed effects at the lender and year-quarter level, re-estimated under alternative definitions of how long a coworker tie remains active. The dependent variable is the midpoint growth rate, transformed into percentage points, for a bank's quarterly lead-arranged lending volume. Columns (1)–(3) use total lending volume, Columns (4)–(6) its non-investment-grade component and Columns (7)–(9) its investment-grade component. Within each block, the first column includes lender and year-quarter fixed effects, the second replaces the lender fixed effects with saturated lender-year fixed effects and the third adds time-varying lender controls (the inverse hyperbolic sine transformations of total assets, net income, number of employees, EBIT, capital expenditure, total liabilities, short- and long-term debt and equity). Each panel recomputes $InflowsAtTies_{it}$ under a different tie window: *Panel A* is the baseline (ties active 4 to 12 quarters after a coworker transition, reproducing Table 1), *Panel B* uses 2 to 12 quarters and *Panel C* uses 4 to 20 quarters. The data span 1994 to 2020. Standard errors are two-way clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A17: Effect of Outside Options on Changes in Financial Risk, Separate Lending at Ties Controls

	VaR 95%		CoVaR 95%		VaR 99%		CoVaR 99%	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Total Syndicated Lending at Ties								
IAT	0.245	0.520*	0.262*	0.509**	0.353*	0.795***	0.356**	0.775***
	(0.197)	(0.287)	(0.156)	(0.238)	(0.183)	(0.301)	(0.159)	(0.262)
Lending at ties, level	X	X	X	X	X	X	X	X
Lending at ties, annual growth	X	X	X	X	X	X	X	X
Panel B. Leveraged Lending at Ties, Spread Definition								
IAT	0.252	0.519*	0.276*	0.515**	0.377**	0.806***	0.383**	0.788***
	(0.198)	(0.289)	(0.156)	(0.237)	(0.184)	(0.302)	(0.160)	(0.262)
Lending at ties, level	X	X	X	X	X	X	X	X
Lending at ties, annual growth	X	X	X	X	X	X	X	X
Panel C. Leveraged Lending at Ties, Rating Definition								
IAT	0.262	0.513*	0.272*	0.489**	0.390**	0.813***	0.388**	0.783***
	(0.199)	(0.287)	(0.158)	(0.236)	(0.187)	(0.301)	(0.162)	(0.261)
Lending at ties, level	X	X	X	X	X	X	X	X
Lending at ties, annual growth	X	X	X	X	X	X	X	X
Panel D. Leveraged Lending at Ties, Loan Purpose Definition								
IAT	0.250	0.541*	0.258*	0.517**	0.369**	0.825***	0.365**	0.795***
	(0.193)	(0.286)	(0.151)	(0.236)	(0.182)	(0.297)	(0.159)	(0.259)
Lending at ties, level	X	X	X	X	X	X	X	X
Lending at ties, annual growth	X	X	X	X	X	X	X	X
Lender FE	X		X		X		X	
Lender × Year FE		X		X		X		X
Year-Quarter FE	X	X	X	X	X	X	X	X
Observations	18,680	18,499	18,680	18,499	18,680	18,499	18,680	18,499

Notes: The table re-estimates the financial risk regressions of Table 2. Each panel jointly controls for the standardized exposure-weighted level and annual growth rate of one lending measure at connected banks. Panel A uses total syndicated lending. Panel B defines leveraged lending using spreads of at least 200 basis points. Panel C uses borrowers rated below investment grade. Panel D uses loan purposes associated with buyouts, mergers and acquisitions and recapitalizations. The dependent variables, fixed effects and sample follow Table 2. Standard errors are two-way clustered at the lender and year-quarter levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A18: Effect of Outside Options on Changes in Financial Risk, Additional Robustness

	VaR 95%			CoVaR 95%			VaR 99%			CoVaR 99%		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A. Adding Inflows at Co-Signatories												
IAT	0.183	0.392	0.248	0.195	0.384*	0.225	0.315**	0.711**	0.472***	0.318***	0.695***	0.452***
	(0.180)	(0.272)	(0.210)	(0.140)	(0.225)	(0.160)	(0.140)	(0.277)	(0.157)	(0.114)	(0.244)	(0.130)
IAC	X	X	X	X	X	X	X	X	X	X	X	X
Observations	18,680	18,499	12,096	18,680	18,499	12,096	18,680	18,499	12,096	18,680	18,499	12,096
Panel B. Excluding 2007–2008												
IAT	0.307**	0.647**	0.419***	0.263**	0.575***	0.344***	0.436***	0.990***	0.642***	0.407***	0.934***	0.591***
	(0.144)	(0.251)	(0.131)	(0.114)	(0.206)	(0.090)	(0.150)	(0.276)	(0.162)	(0.131)	(0.244)	(0.137)
Observations	16,678	16,503	10,234	16,678	16,503	10,234	16,678	16,503	10,234	16,678	16,503	10,234
Lender FE	X		X	X		X	X		X	X		X
Year-Quarter FE	X	X	X	X	X	X	X	X	X	X	X	X
Lender×Year FE		X			X			X			X	
Lender Controls			X			X			X			X

Notes: The table reports additional robustness checks for the financial risk regressions in Table 2. Within each outcome block, the first two specifications follow Table 2 and the third adds time-varying lender controls. Panel A adds Inflows at Co-Signatories, *IAC*. Panel B excludes 2007 and 2008. The data span 1994 to 2009. Standard errors are two-way clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A19: Outside Options and Financial Risk by Seniority

	VaR 95%			CoVaR 95%			VaR 99%			CoVaR 99%		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A. Original IAT												
IAT	0.167	0.479*	0.226	0.173	0.439**	0.179	0.314**	0.783***	0.422***	0.314***	0.741***	0.385***
	(0.194)	(0.263)	(0.253)	(0.150)	(0.215)	(0.192)	(0.145)	(0.235)	(0.160)	(0.115)	(0.211)	(0.128)
Observations	15,823	15,755	11,905	15,823	15,755	11,905	15,823	15,755	11,905	15,823	15,755	11,905
Panel B. OO – medium seniority												
IAT	0.175	0.485*	0.231	0.177	0.436**	0.177	0.313**	0.767***	0.426***	0.309**	0.716***	0.384***
	(0.195)	(0.259)	(0.252)	(0.149)	(0.212)	(0.191)	(0.148)	(0.237)	(0.159)	(0.118)	(0.213)	(0.126)
Observations	15,823	15,755	11,905	15,823	15,755	11,905	15,823	15,755	11,905	15,823	15,755	11,905
Panel C. OO – high seniority												
IAT	0.110	0.363	0.177	0.135	0.371*	0.165	0.282**	0.705***	0.353**	0.298***	0.703***	0.342**
	(0.176)	(0.240)	(0.229)	(0.142)	(0.201)	(0.175)	(0.126)	(0.205)	(0.158)	(0.104)	(0.187)	(0.138)
Observations	15,823	15,755	11,905	15,823	15,755	11,905	15,823	15,755	11,905	15,823	15,755	11,905
Lender FE	X		X	X		X	X		X	X		X
Year-Quarter FE	X	X	X	X	X	X	X	X	X	X	X	X
Lender × Year FE		X			X			X			X	
Lender Controls			X			X			X			X

Notes: The table reports coefficients from OLS regressions of midpoint growth rates in VaR and CoVaR, transformed into percentage points, on standardized IAT. The outcomes are VaR at the 95% confidence level in Columns (1)–(3), CoVaR at the 95% confidence level in Columns (4)–(6), VaR at the 99% confidence level in Columns (7)–(9) and CoVaR at the 99% confidence level in Columns (10)–(12). Panel A uses the original IAT. Panel B recomputes IAT from job-to-job hires with seniority levels 4–5 and Panel C recomputes IAT from job-to-job hires with seniority levels 6–7. Within each panel, IAT is standardized in the estimation sample. Within each outcome block, the first column includes lender and year-quarter fixed effects, the second replaces lender fixed effects with saturated lender-year fixed effects and the third includes lender and year-quarter fixed effects plus time-varying lender controls. Lender controls are the inverse hyperbolic sine transformations of total assets, net income, number of employees, EBIT, capital expenditure, total liabilities, short- and long-term debt and equity. The data are at quarterly frequency and span 1994 to 2009. Standard errors are two-way clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A20: Effect of Outside Options on Changes in Financial Risk, Tie Length Robustness

	VaR 95%			CoVaR 95%			VaR 99%			CoVaR 99%		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A. Baseline: ties active 4 to 12 quarters												
IAT	0.167	0.479*	0.226	0.173	0.439**	0.179	0.314**	0.783***	0.422***	0.314***	0.741***	0.385***
	(0.194)	(0.263)	(0.253)	(0.150)	(0.215)	(0.192)	(0.145)	(0.235)	(0.160)	(0.115)	(0.211)	(0.128)
Observations	15,823	15,755	11,905	15,823	15,755	11,905	15,823	15,755	11,905	15,823	15,755	11,905
Panel B. Ties active 2 to 12 quarters												
IAT	0.189	0.418*	0.251	0.190	0.426**	0.208	0.316**	0.664***	0.420***	0.312***	0.660***	0.385***
	(0.159)	(0.233)	(0.216)	(0.130)	(0.200)	(0.174)	(0.121)	(0.232)	(0.152)	(0.104)	(0.220)	(0.130)
Observations	15,823	15,755	11,905	15,823	15,755	11,905	15,823	15,755	11,905	15,823	15,755	11,905
Panel C. Ties active 4 to 20 quarters												
IAT	0.223	0.485	0.399*	0.307**	0.500**	0.322*	0.208	0.594*	0.414**	0.249	0.594**	0.354**
	(0.185)	(0.313)	(0.220)	(0.124)	(0.247)	(0.174)	(0.204)	(0.315)	(0.194)	(0.151)	(0.266)	(0.174)
Observations	15,983	15,915	12,033	15,983	15,915	12,033	15,983	15,915	12,033	15,983	15,915	12,033
Lender FE	X		X	X		X	X		X	X		X
Year-Quarter FE	X	X	X	X	X	X	X	X	X	X	X	X
Lender×Year FE		X			X			X			X	
Lender Controls			X			X			X			X

Notes: The table reports coefficients from OLS regressions of midpoint growth rates in VaR and CoVaR (in percentage points) on standardized $InflowsAtTies_{it}$, re-estimated under alternative definitions of how long a coworker tie remains active. The outcomes are VaR at the 95% confidence level (Columns 1–3), CoVaR at the 95% confidence level (Columns 4–6), VaR at the 99% confidence level (Columns 7–9) and CoVaR at the 99% confidence level (Columns 10–12). Within each outcome block, the first column includes lender and year-quarter fixed effects, the second replaces lender fixed effects with saturated lender-year fixed effects and the third includes lender and year-quarter fixed effects plus time-varying lender controls. Lender controls are the inverse hyperbolic sine transformations of total assets, net income, number of employees, EBIT, capital expenditure, total liabilities, short- and long-term debt and equity. Each panel recomputes $InflowsAtTies_{it}$ under a different tie window: *Panel A* is the baseline (ties active 4 to 12 quarters after a coworker transition, reproducing Table 2), *Panel B* uses 2 to 12 quarters and *Panel C* uses 4 to 20 quarters. The data are at quarterly frequency and span 1994 to 2009. Standard errors are two-way clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A21: Effect of Outside Options on Borrower Risk, Separate Lending at Ties Controls

	Below-Investment-Grade Borrower, percentage points				
	(1)	(2)	(3)	(4)	(5)
Panel A. Total Syndicated Lending at Ties					
IAT	0.611***	0.586***	0.616***	1.257***	1.214***
	(0.127)	(0.191)	(0.180)	(0.351)	(0.402)
Lending at ties, level	X	X	X	X	X
Lending at ties, annual growth	X	X	X	X	X
Panel B. Leveraged Lending at Ties, Spread Definition					
IAT	0.650***	0.608***	0.639***	1.281***	1.237***
	(0.124)	(0.198)	(0.184)	(0.365)	(0.409)
Lending at ties, level	X	X	X	X	X
Lending at ties, annual growth	X	X	X	X	X
Panel C. Leveraged Lending at Ties, Rating Definition					
IAT	0.612***	0.586***	0.600***	1.261***	1.187***
	(0.131)	(0.188)	(0.175)	(0.361)	(0.389)
Lending at ties, level	X	X	X	X	X
Lending at ties, annual growth	X	X	X	X	X
Panel D. Leveraged Lending at Ties, Loan Purpose Definition					
IAT	0.605***	0.580***	0.622***	1.270***	1.243***
	(0.136)	(0.187)	(0.178)	(0.353)	(0.403)
Lending at ties, level	X	X	X	X	X
Lending at ties, annual growth	X	X	X	X	X
Lender FE	X				
Lender × Year FE		X	X	X	X
Year-Quarter FE	X	X			
Borrower Sector × Year-Quarter FE			X		X
Borrower State × Year-Quarter FE				X	X
Lender, Borrower, Loan Controls	X	X	X	X	X
Observations	55,327	55,278	55,223	50,082	50,045

Notes: The table re-estimates the borrower risk regressions of Table 3. Each panel jointly controls for the standardized exposure-weighted level and annual growth rate of one lending measure at connected banks. Panel A uses total syndicated lending. Panel B defines leveraged lending using spreads of at least 200 basis points. Panel C uses borrowers rated below investment grade. Panel D uses loan purposes associated with buyouts, mergers and acquisitions and recapitalizations. The dependent variable, controls, fixed effects and sample follow Table 3. Standard errors are two-way clustered at the lender and year-quarter levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A22: Effect of Outside Options on Borrower Risk, Robustness

Robustness	Additional Control		Sample / Variable		
	Nr. Lenders	IAC	Origination	Excl. GFC	Winsor.
	Non-Prime Borrower (pp)				
	(1)	(2)	(3)	(4)	(5)
IAT	1.260***	1.472***	1.688***	4.014***	3.150**
	(0.407)	(0.366)	(0.412)	(1.481)	(1.364)
Lender × Year FE	X	X	X	X	X
Borrower Sector × Year-Quarter FE	X	X	X	X	X
Borrower State × Year-Quarter FE	X	X	X	X	X
Lender, Borrower, Loan Controls	X	X	X	X	X
Number of Lenders	X				
IAC		X			
Observations	50,045	45,542	21,625	46,730	50,045

Notes: The table reports robustness exercises for the borrower risk result in Table 3, estimated using the fully saturated specification in Column (5). Column (1) controls for the number of lenders in the syndicate and Column (2) controls for Inflows at Co-Signatories, IAC. Column (3) restricts the sample to newly originated loans, Column (4) excludes 2007 and 2008 and Column (5) winsorizes $InflowsAtTies_{it}$ at the 1st and 99th percentiles. All specifications include lender-year, borrower-sector-by-year-quarter and borrower-state-by-year-quarter fixed effects as well as lender, borrower and loan controls. The dependent variable is an indicator for a borrower rated below investment grade multiplied by 100. Standard errors are two-way clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A23: Outside Options and Borrower Risk by Seniority

	Non-Prime Borrower (ex ante, pp)			
	(1)	(2)	(3)	(4)
Panel A. Original IAT				
IAT	0.475***	0.583***	0.622***	1.258***
	(0.147)	(0.178)	(0.176)	(0.382)
Observations	55,327	55,278	55,223	50,045
Panel B. OO – medium seniority				
IAT	0.439***	0.543***	0.593***	1.170***
	(0.140)	(0.166)	(0.169)	(0.349)
Observations	55,327	55,278	55,223	50,045
Panel C. OO – high seniority				
IAT	0.783**	0.931**	0.786*	1.770***
	(0.297)	(0.375)	(0.417)	(0.634)
Observations	55,327	55,278	55,223	50,045
Lender FE	X			
Year-Quarter FE	X	X		
Lender × Year FE		X	X	X
Borrower Sector × Year-Quarter FE			X	X
Borrower State × Year-Quarter FE				X
Lender, Borrower, Loan Controls	X	X	X	X

Notes: The table reports loan-level linear probability regressions in which the dependent variable is an indicator equal to one if the borrower is rated below investment grade by S&P multiplied by 100, so a positive coefficient indicates a percentage point shift toward riskier borrowers. Panel A uses the original IAT. Panel B recomputes IAT from job-to-job hires with seniority levels 4–5 and Panel C recomputes IAT from job-to-job hires with seniority levels 6–7. IAT is standardized within each panel's estimation sample. All columns include the full set of borrower, lender and loan controls. Column (1) includes additive lender and year-quarter fixed effects. Column (2) replaces the lender fixed effect with lender-year fixed effects. Column (3) adds borrower-sector-by-year-quarter fixed effects and Column (4) further adds borrower-state-by-year-quarter fixed effects. Borrower and lender controls are the inverse hyperbolic sine transformations of total assets, capital expenditure, number of employees, total liabilities, EBIT, net income, current debt, long-term debt and equity. Loan controls are the inverse hyperbolic sine of tranche amount and maturity and indicators for whether the loan is secured and whether covenants are attached. The data span 1994 to 2020. Standard errors are two-way clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A24: Effect of Outside Options on Borrower Risk, Tie Length Robustness

	Non-Prime Borrower, percentage points			
	(1)	(2)	(3)	(4)
Panel A. Baseline, ties active 4 to 12 quarters				
IAT	0.475***	0.583***	0.622***	1.258***
	(0.147)	(0.178)	(0.176)	(0.382)
Observations	55,327	55,278	55,223	50,045
Panel B. Ties active 2 to 12 quarters				
IAT	0.484***	0.655***	0.692***	1.269***
	(0.143)	(0.209)	(0.205)	(0.364)
Observations	55,327	55,278	55,223	50,045
Panel C. Ties active 4 to 20 quarters				
IAT	0.618***	0.461**	0.484***	0.943***
	(0.124)	(0.180)	(0.129)	(0.327)
Observations	55,327	55,278	55,223	50,045
Lender FE	X			
Year-Quarter FE	X	X		
Lender × Year FE		X	X	X
Borrower Sector × Year-Quarter FE			X	X
Borrower State × Year-Quarter FE				X
Lender, Borrower, Loan Controls	X	X	X	X

Notes: The table reports the loan-level borrower-risk regression of Equation (15) across a set of increasingly demanding fixed effects, re-estimated under alternative definitions of how long a coworker tie remains active. The below-investment-grade indicator is multiplied by 100 before estimation, so coefficients are in percentage points and a positive coefficient indicates a shift toward riskier borrowers. $InflowsAtTies_{it}$ is standardized and all columns include the full set of borrower, lender and loan controls. Column (1) includes additive lender and year-quarter fixed effects. Column (2) replaces the lender fixed effect with lender-year fixed effects. Column (3) adds borrower-sector-by-year-quarter fixed effects. Column (4) further adds borrower-state-by-year-quarter fixed effects. Borrower and lender controls are the inverse hyperbolic sine transformations of total assets, capital expenditure, number of employees, total liabilities, EBIT, net income, current debt, long-term debt and equity. Loan controls are the inverse hyperbolic sine of tranche amount and maturity and indicators for whether the loan is secured and whether covenants are attached. Each panel recomputes $InflowsAtTies_{it}$ under a different tie window: *Panel A* is the baseline (ties active 4 to 12 quarters after a coworker transition, reproducing Table 3), *Panel B* uses 2 to 12 quarters and *Panel C* uses 4 to 20 quarters. The estimation sample is held fixed across panels. The data span 1994 to 2020. Standard errors are two-way clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A25: First-Difference Specification

	Δ Non-Prime Loan Share, percentage points	
	(1)	(2)
Δ Inflows at Ties	1.396***	
	(0.426)	
$\sum_j s_{ij,t-1}\,\Delta Inflows_{jt}$, fixed exposure		2.764*
		(1.384)
Year-quarter FE	X	X
Observations	1,956	1,956

Notes: The table reports first-difference estimates relating outside-option shocks to borrower risk, as a robustness check for the panel's time-varying shares (Borusyak et al., 2022). The below-investment-grade loan share in a lender-quarter is multiplied by 100 before first-differencing and estimation, so coefficients are in percentage points and a positive coefficient indicates a shift toward riskier borrowers. Column (1) regresses the change in the risky loan share on the change in standardized inflows at ties. Column (2) replaces this regressor with a fixed-exposure first-difference shift-share measure, $\sum_j s_{ij,t-1}\,\Delta Inflows_{jt}$, where $\Delta Inflows_{jt}$ is the change in the total number of job-to-job inflows of senior finance workers into connected bank j from quarter $t-1$ to quarter t, which applies prior-quarter exposure weights to changes in hiring at connected banks. This construction removes variation generated by quarterly changes in the network weights. Both regressors are standardized separately. All specifications absorb year-quarter fixed effects. Standard errors clustered at the lender level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A26: Effect of Outside Options on Misconduct Disclosures

	Misconduct						Binarized (pp)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IAT_{t-2}					-0.001		
					(0.001)		
IAT_{t-1}	0.003***	0.003***	0.003***	0.003***	0.002***	0.004***	0.328***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.052)
IAT_{t}					0.003		
					(0.002)		
Outflows_{t-1}						0.003**	
						(0.001)	
Lender fixed effects	X	X					
Year fixed effects	X	X	X		X	X	X
Adviser fixed effects		X					
Lender × Adviser fixed effects			X	X	X	X	X
State × Year fixed effects				X			
Lender Controls	X	X	X	X	X	X	X
Observations	582,568	561,018	551,079	551,079	551,079	551,079	551,079

Notes: The table reports results from estimating Equation (15) at annual frequency at the advisor level. Columns (1)–(6) use the number of misconduct disclosures on its original count scale. Column (7) uses an indicator for any misconduct disclosure multiplied by 100 before estimation, so its coefficient is in percentage points. The main independent variable is $InflowsAtTies_{it-1}$. Lender controls are the inverse hyperbolic sine transformations of total assets, net income, number of employees, EBIT, capital expenditure, total liabilities, short- and long-term debt, equity and the first lag of the firm-level average of the outcome variable. Column (5) includes contemporaneous inflows at ties and its second lag. Column (6) controls for the inverse hyperbolic sine transformation of lagged outflows. All models include lender controls. Column (1) includes lender and year fixed effects. Column (2) adds advisor fixed effects. Columns (3) and (5)–(7) include lender-advisor and year fixed effects. Column (4) includes lender-advisor and state-year fixed effects. Standard errors are two-way clustered by lender and calendar year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A27: Effect of Outside Options on Customer Complaints

	Complaints						Binarized (pp)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IAT_{t-2}					0.000		
					(0.002)		
IAT_{t-1}	0.005***	0.006***	0.006***	0.005***	0.003**	0.006***	0.417***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.119)
IAT_{t}					0.005		
					(0.003)		
$Outflows_{t-1}$						0.003	
						(0.005)	
Lender fixed effects	X	X					
Year fixed effects	X	X	X		X	X	X
Adviser fixed effects		X					
Lender × Adviser fixed effects			X	X	X	X	X
State × Year fixed effects				X			
Lender Controls	X	X	X	X	X	X	X
Observations	582,568	561,018	551,079	551,079	551,079	551,079	551,079

Notes: The table reports results from estimating Equation (15) at annual frequency at the advisor level. Columns (1)–(6) use the number of customer complaints on its original count scale. Column (7) uses an indicator for any customer complaint multiplied by 100 before estimation, so its coefficient is in percentage points. The main independent variable is $InflowsAtTies_{it-1}$. Lender controls are the inverse hyperbolic sine transformations of total assets, net income, number of employees, EBIT, capital expenditure, total liabilities, short- and long-term debt, equity and the first lag of the firm-level average of the outcome variable. Column (5) includes contemporaneous inflows at ties and its second lag. Column (6) controls for the inverse hyperbolic sine transformation of lagged outflows. All models include lender controls. Column (1) includes lender and year fixed effects. Column (2) adds advisor fixed effects. Columns (3) and (5)–(7) include lender-advisor and year fixed effects. Column (4) includes lender-advisor and state-year fixed effects. Standard errors are two-way clustered by lender and calendar year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A28: Effect of Outside Options on Settled Customer Complaints

	Complaints (Settled)						Binarized (pp)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IAT_{t-2}					0.000		
					(0.001)		
IAT_{t-1}	0.004***	0.004**	0.004**	0.004***	0.003	0.004**	0.326**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.132)
IAT_{t}					0.004		
					(0.002)		
Outflows_{t-1}						0.003*	
						(0.002)	
Lender fixed effects	X	X					
Year fixed effects	X	X	X		X	X	X
Adviser fixed effects		X					
Lender × Adviser fixed effects			X	X	X	X	X
State × Year fixed effects				X			
Lender Controls	X	X	X	X	X	X	X
Observations	582,568	561,018	551,079	551,079	551,079	551,079	551,079

Notes: The table reports results from estimating Equation (15) at annual frequency at the advisor level. Columns (1)–(6) use the number of settled customer complaints on its original count scale. Column (7) uses an indicator for any settled customer complaint multiplied by 100 before estimation, so its coefficient is in percentage points. The main independent variable is $InflowsAtTies_{it-1}$. Lender controls are the inverse hyperbolic sine transformations of total assets, net income, number of employees, EBIT, capital expenditure, total liabilities, short- and long-term debt, equity and the first lag of the firm-level average of the outcome variable. Column (5) includes contemporaneous inflows at ties and its second lag. Column (6) controls for the inverse hyperbolic sine transformation of lagged outflows. All models include lender controls. Column (1) includes lender and year fixed effects. Column (2) adds advisor fixed effects. Columns (3) and (5)–(7) include lender-advisor and year fixed effects. Column (4) includes lender-advisor and state-year fixed effects. Standard errors are two-way clustered by lender and calendar year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A29: Effect of Outside Options on Labor Market Disciplining

	Job Separation (pp)		Leave Industry (pp)				Reemployment Next Year (pp)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Misconduct	42.480***	44.309***	23.692***	23.935***	0.395	0.314	-0.598	-0.393
	(5.008)	(5.317)	(4.080)	(3.773)	(0.984)	(0.806)	(1.278)	(1.027)
Misconduct × IAT_{t-1}	-7.542*	-8.627**	-5.395**	-5.513**	0.134	0.157	-0.245	-0.333
	(3.686)	(3.547)	(1.956)	(1.849)	(0.397)	(0.371)	(0.437)	(0.443)
Misconduct × IAT_t	1.456	1.806	1.812	1.766	-0.013	-0.063	0.191	0.285
	(4.457)	(4.440)	(2.733)	(2.576)	(0.336)	(0.282)	(0.431)	(0.293)
Job Separation × Misconduct					13.302	12.716	-14.003	-12.673
					(7.443)	(7.808)	(8.728)	(8.924)
Job Separation × IAT_{t-1}					-4.041*	-3.292***	3.192	2.238**
					(2.011)	(0.576)	(1.996)	(0.858)
Job Separation × IAT_t					-1.512	0.222	2.752	1.412
					(2.660)	(1.496)	(2.352)	(1.632)
Job Separation × Misconduct × IAT_{t-1}					-6.779***	-6.134**	7.688***	7.248***
					(0.912)	(1.895)	(1.446)	(2.050)
Job Separation × Misconduct × IAT_t					5.287*	4.283	-5.662	-5.148
					(2.624)	(2.948)	(3.390)	(3.370)
Adviser fixed effects	X		X		X		X	
Lender × Year fixed effects	X	X	X	X	X	X	X	X
Lender × Adviser fixed effects		X		X		X		X
Observations	598,839	589,763	598,839	589,763	598,839	589,763	598,839	589,763

Notes: The table reports versions of Equation (17) estimated at annual frequency at the advisor level. The dependent variables are multiplied by 100 before estimation, so coefficients are in percentage points. The outcomes indicate whether the advisor is no longer employed at firm i in year $t+1$ in Columns (1) and (2), is no longer recorded in the sample in Columns (3) to (6) or is employed at another sample firm in year $t+1$ in Columns (7) and (8). The independent variables are contemporaneous and lagged inflows at ties, an indicator for a misconduct disclosure in year t and the interactions shown in the table. Columns (1) to (4) estimate the unconditional consequences of misconduct. Columns (5) to (8) fully interact separation, misconduct, contemporaneous IAT and lagged IAT to estimate industry exit and reemployment conditional on separation. All specifications include firm-year fixed effects. Odd-numbered columns include advisor fixed effects, while even-numbered columns include firm-advisor fixed effects. Standard errors are two-way clustered by firm and calendar year. The figure in the main text uses the even-numbered specifications and reports total marginal effects evaluated with contemporaneous IAT at its mean and lagged IAT one standard deviation below or above its mean. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.