# Bankers' Outside Options And Financial Risk*

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**Abstract**

This paper documents that bankers with better labor market outside options take more financial risk. We use granular employment history data to construct a bank-level measure of outside options that captures labor demand shocks at connected financial institutions. Banks with workers exposed to improved outside options expand lending volumes by shifting toward riskier borrowers, raising financial risk at both the bank and system level. These patterns are not driven by yield-seeking or demand-side factors, and are instead consistent with a framework in which outside options insure bankers against adverse outcomes, weakening the disciplinary role of dismissal risk. We provide evidence for this mechanism using individual-level data on bankers' lending decisions and information on financial advisor misconduct. As outside options are procyclical, our results point to a labor mobility channel through which labor market conditions contribute to aggregate fluctuations in credit supply.

**Keywords:** Financial Stability, Risk, Labor Markets, Outside Options

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# 1 Introduction

In imperfect labor markets, workers' outside options play a central role in determining wages and job mobility. Improvements in the quality or quantity of alternative employment opportunities strengthen workers' bargaining positions, translating into higher pay and more frequent transitions across employers (Caldwell and Harmon, 2019; Caldwell and Danieli, 2024; Johnson et al., 2025). However, outside options may not only affect workers' matching to firms, but also their actions within firms. We investigate the link between outside options and on-the-job behavior in the context of the financial industry, a setting well suited to study this question for two reasons. First, job-to-job transitions represent a relatively high share of new hires in the financial sector (Azzopardi et al., 2020). Bankers should consequently attend closely to the on-the-job arrival of offers, making their conduct inside the firm sensitive to the state of the external labor market. Second, employees have considerable discretion in making risky, high-stakes choices on behalf of their firms, which have limited capacity to monitor these decisions.

We present empirical evidence that bankers with better labor market outside options make riskier lending decisions and argue that an insurance channel drives these results: improved outside options reduce the alignment of interests between workers and firms, as they undercut the disciplinary role of dismissal. Because employment opportunities are procyclical, this effect varies systematically over the business cycle and can contribute to fluctuations in credit supply. Given the large, negative spillovers of financial crises, these dynamics in a narrow segment of the labor market can carry consequences well beyond the firms involved.

To formalize this mechanism, we develop a stylized model in which a risk-averse banker chooses the risk level of their loan portfolio, balancing higher expected returns against greater payoff volatility. The banker faces a stochastic labor market outside option that is realized after the risk choice. The presence of this outside option truncates the distribution of potential payoffs from below, implying that the banker is partly insured against adverse portfolio realizations. As a result, the outside option reduces effective risk aversion and distorts incentives by weakening the downside consequences of failure. The main prediction of the model is that exogenous improvements in outside options lead bankers to make riskier lending decisions.[1]

[1] This mechanism parallels the logic of the literature on state guarantees, which has documented increased risk-taking among banks as a response to state-provided insurance (Brandao-Marques et al., 2013; Dam and Koetter, 2012;

In testing this prediction empirically, the key challenge is to identify shocks to outside options that are exogenous to contemporaneous bank-level dynamics. For instance, a natural proxy for outside options is the rate at which workers are departing for other banks, as it plausibly reflects their current employment opportunities. However, as outflows may also respond to the bank's own financial conditions, a negative shock to a bank could raise outflows while depressing credit supply, generating a spurious negative correlation between the two variables. To address this concern, we construct a measure of outside options that is orthogonal to a bank's own contemporaneous dynamics. Specifically, we use individual employment biographies of senior US investment bankers to create a network-based measure, capturing labor demand at other banks. This approach rests on the idea that information about hiring dynamics is transmitted through coworker networks. By exploiting variation in the strength of ties between banks, we measure the differential exposure of workers across banks to labor demand at other institutions. In a series of validation exercises, we show that our measure of outside options is orthogonal to past employee outflows as well as to contemporaneous and past bank-level financial fundamentals. Consistent with prior literature, the measure is also predictive of both worker transitions to other firms and compensation gains for the remaining workers.

In our main empirical analysis, we examine how bankers' outside options affect their lending decisions and the resulting financial risk. With the inclusion of fixed effects at the bank and year-quarter level, we isolate within-bank variation from bank level differences as well as aggregate shifts in risk attitude over time. Drawing on transaction-level data on syndicated loans, our results indicate that banks expand lending volumes in response to improved outside options by arranging more loans. This credit expansion is accompanied by higher value at risk, a bank-level risk measure, with effects concentrated in the tail of the loss distribution. Importantly, these effects are not confined to individual banks, as improved outside options also raise a bank's contribution to systemic risk at high levels of distress.

We then scrutinize the loan-level dynamics underlying these patterns and find that the credit expansion reflects a shift toward riskier borrowers. Focusing on the likelihood that a borrower is rated investment-grade, a one standard deviation increase in outside options reduces the share of

Bianchi, 2016), with negative implications for financial stability (Diamond and Rajan, 2002; Demirgüç-Kunt and Detragiache, 2002). However, in our context, the insurance mechanism operates through markets at the level of individual bankers rather than through governments at the level of banks.

prime borrowers by 1.7% of its mean. This deterioration in borrower quality is not compensated by higher spreads, which is difficult to reconcile with yield-seeking behavior and rather points to an increase in risk-taking. We further demonstrate that our result is robust to controlling for information flows between employers. Finally, we corroborate these findings by leveraging differences in the enforceability of non-compete agreements (NCAs) in the bank's headquarter state, showing that the response in loan-level risk to outside options is concentrated in states where NCA enforceability has fallen. Given that weaker enforceability makes outside options more readily exercisable, this pattern suggests that bankers respond to improved outside options only when these map into realistic mobility opportunities.

Turning to the underlying mechanism, we provide two sets of results showing that improved outside options increase bankers' willingness to take risk by offering implicit insurance against adverse outcomes. First, we link individual loans to underwriting bankers and study heterogeneity across bankers' characteristics. Conditional on banker and bank-year fixed effects, the effects are concentrated among younger bankers, who are most exposed to dismissal risk. This result is consistent with the insurance channel and suggests that the effect we identify is not driven by senior poaching or team lift-outs, which would predict the inverse age gradient. Second we extend the analysis to the market for financial advisors, where we find that misconduct becomes more prevalent when outside options improve. Better outside options also partly offset the disciplinary effects of layoffs. Following misconduct, they reduce the probability of job separation and, even conditional on separation, increase the likelihood of reemployment in the same sector. This state-dependence indicates that stronger labor markets weaken the disciplinary force of job loss, the mechanism at the heart of the insurance channel.

These results also speak to aggregate dynamics. As documented in Figure A1, labor mobility in the financial sector is closely associated with lending standards over time. By offering a micro-foundation for this relationship, we identify a worker-level channel through which labor market conditions translate into systematic variation in credit supply. Because outside options are generally considered procyclical in both theoretical and empirical accounts (Mortensen and Pissarides, 1999; Nakamura et al., 2019; Figueiredo, 2022), real economic shocks that expand both credit demand and competition over banking talent can reinforce one another, contributing to excess lending during expansions. Due to the role of credit growth in increasing both the likelihood and

the severity of financial crises (Schularick and Taylor, 2012; Jordà et al., 2013), our findings point to a neglected role of labor markets in macroprudential policy.

**Literature:** Our main contribution is to provide empirical evidence on a novel mechanism through which labor markets affect credit supply, adding to four strands of literature. First, a small theoretical literature has studied potential interactions between agency problems within banks, labor market dynamics in the financial sector, and the quality and quantity of credit (Myerson, 2012, 2014; Thanassoulis, 2012; Axelson and Bond, 2015; Acharya et al., 2016; Boxtel, 2017). These papers analyze different channels through which the labor market for bankers can impact credit supply, including frictions in the supply of bankers, externalities generated by competition for talent, and bankers' job opportunities outside the financial sector. We add to this literature by providing empirical evidence on this interaction, and in particular on a channel whereby hiring at one bank, by improving the outside options of bankers elsewhere, weakens their alignment with their own employer.

Second, we inform the discussion about the role of career concerns in mitigating risky behavior in the financial sector, which can be traced back to the seminal work of Holmström (1999). The evidence on whether bankers are punished for adverse choices is mixed: some studies report no effect in response to corporate misconduct (Griffin et al., 2019; Hamdi et al., 2023), while others detect such effects in the context of syndicated loans and hedge funds (Ellul et al., 2020; Gao et al., 2020). Our study complements these findings by showing that the career consequences of risky choices vary with outside options, and that bankers internalize this state-dependence.

Third, a related empirical literature has examined different aspects of the labor market in the financial sector, such as the high labor mobility of investment bankers (Gao et al., 2024a,b) and the effect of labor mobility restrictions on financial intermediation (Cici et al., 2021; Agarwal et al., 2024; Bonelli, 2019; Norden et al., 2025). Other papers have highlighted the discretionary role of individual bankers in setting lending terms for syndicated loans (Herpfer, 2021; Bushman et al., 2021; Carvalho et al., 2023). We contribute to this literature by showing that labor mobility across firms can lead to the origination of more credit, more risky credit, and more financial risk in the context of corporate lending.

Finally, our paper speaks to a recent literature examining the role of outside options in labor markets more generally (Caldwell and Danieli, 2024; Caldwell et al., 2024; Schubert et al., 2022). In particular, Jäger et al. (2024) show that information from coworkers shifts worker beliefs about outside options, which in turn affect their search and bargaining behavior. Caldwell and Harmon (2019) investigate the role of personal networks in transmitting such information about outside options across firms, showing that news transmitted through these networks promotes both wage growth and labor mobility. Ahammer et al. (2023) document a negative relationship between outside options and worker effort by exploiting variation in unemployment insurance. We add to this work by documenting that outside options shape the job-related decisions of high-skilled workers through a risk-taking channel, with potentially adverse implications for their employers.

The structure of the paper is as follows: Section 2 lays out the conceptual framework and main predictions, followed by Section 3, which details the data. Section 4 describes our outside options measure and identification strategy, and Section 5 presents the results from the syndicated loan market. We examine the underlying insurance mechanism in Section 6, and Section 7 concludes.

## 2 Conceptual Framework

To guide our analysis on how outside options affect risk-taking, we present a stylized framework featuring a banker who chooses optimal portfolio risk in the presence of a random outside option. The key prediction is that better outside options induce higher levels of risk-taking. The intuition behind this result builds on Curello et al. (2025), who show that outside option improvements are equivalent to reductions in effective risk aversion. The latter is defined as the curvature of the utility function that rationalizes a banker's choices once the outside option is taken into account, which differs from their underlying preferences.

While this setup resembles a conventional portfolio-choice problem, it is non-standard. This is because the presence of an outside option changes the selection rule by replacing poor portfolio outcomes with a fallback.[2] The transformation works through the quality of the outside option, summarized by the reverse hazard rate of its distribution, and leaves both the mean and the variance of payoffs unchanged. The standard wealth and variance channels therefore play no

[2]This sets it apart from ordinary background risk, which adds mean-zero noise and typically raises effective risk aversion.

role. The higher the reverse hazard rate, the better the option insures the banker against bad realizations, and the lower their effective risk aversion. We parameterize an application of the framework of Curello et al. (2025) to generate closed-form comparative statics that we bring to the data.

**Setup:** We consider a banker with CARA utility choosing a portfolio risk measure $r \in [0, \bar{r}]$. Both the expected return and payoff risk are increasing in $r$. Specifically, we model portfolio payoffs by a normal approximation,

$$x(r) = \mu_0 + a\,r + \varepsilon, \qquad \varepsilon \sim \mathcal{N}\Big(0,\, v_0 + b\,r^2\Big), \tag{1}$$

with $a > 0$ and $b > 0$. The banker receives a share $y(r) = \alpha x(r)$ of the portfolio returns, with the bank retaining $(1-\alpha)x(r)$. Let baseline utility $v$ be CARA with baseline risk aversion $\sigma > 0$, $v(x) = -\frac{1}{\sigma}e^{-\sigma x}$.

We assume that the outside option is reversed exponential on $(-\infty, 0]$ with rate $\lambda \geq 0$, implying a constant reverse hazard: $G'(x)/G(x) = \lambda$.[3] The labor market outside option is a random payoff $K$ with cumulative distribution $G$, which is continuous and with positive density on its support. That is, the banker knows the distribution of outside option payoffs but is unaware of the realization during the decision-making process. A higher $\lambda$ shifts probability mass of the outside-option distribution toward its upper bound 0, thinning the left tail and making low realizations of $K$ less likely. Intuitively, outside options improve in expectation while becoming less dispersed. To maintain tractability, we assume $K$ is independent of the payoff shock in $x(r)$, ruling out outside options that co-move with the banker's own portfolio outcomes.

The banker chooses $r$ to maximize

$$\max_{r}\ \mathbb{E}\Big[v(\max\{y(r), K\})\Big]. \tag{2}$$

[3]Define $K = -E$ with $E \sim \text{Exp}(\lambda)$. Then $K$ follows a mirrored exponential distribution bounded above by 0, with cumulative distribution function $G(x) = e^{\lambda(x)}$ for $x \leq 0$ and $G(x) = 1$ for $x > 0$. Thus, when $\lambda$ is large, more probability mass lies just below 0. The exponential is the case in which the reverse hazard is constant, which delivers closed-form comparative statics, while more general distributions yield a state-dependent effective risk aversion.

The timing is as follows: the banker chooses $r$, then the payoff shock $\varepsilon$ and the outside option $K$ realize, determining consumption $Y^{\text{eff}} = \max\{y(r), K\}$. As the banker chooses $r$ before $K$ realizes but with full knowledge of its distribution, risk-taking responds to $\lambda$, which captures expectations about the outside option.

**Decomposition:** We show that the outside option generates a CARA representation with effective risk aversion $\sigma - \lambda$. Let $W(y) \equiv \mathbb{E}_K\Big[v(\max\{y, K\})\Big]$ denote the objective function induced by the outside option. Given that $v$ is increasing and twice-differentiable and $G$ has positive density $g$ on its support, differentiation yields

$$W'(y) = \mathbb{E}[v'(\max\{y, K\}) \cdot \mathbf{1}\{K \leq y\}] = v'(y)\, G(y), \tag{3}$$

because an incremental increase in $y$ matters only in states where $y$ binds, that is, where $K \leq y$. Differentiating again and dividing by $W'(y) = v'(y)G(y)$ yields

$$\frac{W''(y)}{W'(y)} = \frac{v''(y)}{v'(y)} + \frac{G'(y)}{G(y)}. \tag{4}$$

Since choices are invariant to positive affine transformations of the objective function, we can take $u(y) = aW(y) + b$ with $a > 0$, which is also CARA with coefficient of absolute risk aversion

$$-\frac{u''(y)}{u'(y)} = \sigma - \lambda. \tag{5}$$

Effective risk aversion $\sigma - \lambda$ is thus strictly below $\sigma$, confirming the intuition above. Only a fraction $G(y)$ of states use $y$ rather than $K$, so marginal utility is effectively scaled by $G(y)$. The second differentiation converts this scaling into an additive term, the reverse hazard rate $\frac{G'(y)}{G(y)}$, which lowers the agent's absolute risk aversion.

**Comparative statics:** The decomposition shows that effective utility $u$ is also CARA with effective absolute risk aversion $\rho = \sigma - \lambda$. That is, improvements in the outside option (higher $\lambda$) translate into a one-for-one reduction of $\rho$. Under CARA–normal, expected utility is summarized

by the certainty equivalent, which takes the form of

$$\mathrm{CE}(r) = \mathbb{E}[y(r)] - \frac{\rho}{2}\mathrm{Var}[y(r)] = \alpha(\mu_0 + ar) - \frac{\rho}{2}\alpha^2\Big(v_0 + br^2\Big). \tag{6}$$

Assuming that $\sigma > \lambda$, maximizing $\mathrm{CE}(r)$ yields

$$\frac{d\,\mathrm{CE}}{dr} = \alpha a - \rho\,\alpha^2 b\,r = 0 \;\Rightarrow\; r^* = \frac{a}{\rho\,\alpha b} = \frac{a}{(\sigma-\lambda)\,\alpha b}$$

$$\frac{\partial r^*}{\partial \lambda} = \frac{a}{b}\frac{1}{\alpha(\sigma-\lambda)^2} > 0 \;\; (\lambda < \sigma). \tag{7}$$

Consistent with standard models, risk-taking increases in the risk sensitivity of returns $a$ and decreases with both the convexity of risk $b$ and the share $\alpha$ accruing to the banker.

Crucially, the framework also predicts that higher levels of $\lambda$ increase the optimal level of risk-taking.[4] A more favorable outside option effectively provides insurance, as the joint probability of bad realizations for the portfolio return and the outside option becomes very small. This truncation of downside risk reduces the effective risk aversion of the banker ($\rho = \sigma - \lambda$). Empirically, we thus expect better outside options to induce greater risk-taking, reflected in higher loan volumes and a lower share of investment-grade borrowers.

While our framework treats outside options as exogenously given, they may in turn depend on the chosen risk level $r$. We abstract from this feedback loop, as our empirical strategy exploits variation in outside options that is orthogonal to individual behavior. The framework also takes $\lambda$ as fixed, whereas outside options are in practice tightly linked to overall labor market conditions. Because outside options are procyclical, risk-taking through this channel co-moves with the credit cycle. As the labor market strengthens during expansions, improved outside options in finance add to the surge in credit demand by further relaxing lending standards. In downturns, the mechanism works in reverse: weaker outside options tighten the implicit insurance, prompting bankers to reduce risk, thereby reinforcing credit contractions. The model thus provides a micro-level channel linking labor market conditions to credit supply over the cycle.

Several additional assumptions are required to arrive at the prediction that better labor market outside options increase credit risk. First, we assume that changes in other banks' hiring behavior

[4] If the interior solution fails, i.e., if $\sigma \leq \lambda$, or equivalently $\rho \leq 0$, the solution is at the upper bound $\bar{r}$.

lead to variation in bankers' outside options. This assumption is relatively weak, as the banking sector experiences limited entry by workers, particularly at mid-to-late career stages (Philippon and Reshef, 2012; Bell and Van Reenen, 2014; Böhm et al., 2023). Moreover, the supply of qualified graduates is likely relatively inelastic in the short run, and senior roles cannot easily be filled by junior bankers. As a result, job-to-job transitions are common in the financial industry. Second, our results hinge on the assumption that individual bankers influence loan decisions. Although loan sizes are substantial in the syndicated loan market, making this effect non-trivial, there is extensive evidence documenting the discretionary role of individual bankers in determining lending terms for syndicated loans (Herpfer, 2021; Bushman et al., 2021; Carvalho et al., 2023). Third, we implicitly assume that banks do not immediately and fully adjust compensation to current labor market conditions in order to offset the adverse effects of improved outside options. To induce less risky lending, a bank could increase the share $\alpha$ of portfolio returns that go to the banker. We treat $\alpha$ as fixed, keeping the determination of compensation contracts outside the model.

While our model focuses on the insurance effect of outside options as alternative employment opportunities, a number of complementary mechanisms could be at play. First, better outside options are likely to increase turnover. As a result, expected tenure decreases, reducing the probability of a loan default occurring during the current employment spell and hence of being punished for excessive risk-taking. The diminished threat of punishment may then incentivize bankers to take on greater risk. As this channel operates through earlier departures to other firms, whereas our insurance mechanism operates even for bankers who stay, controlling for outflows allows us to rule out the former. In a robustness exercise, we find no evidence that turnover accounts for our main results. Second, behavioral factors could also be relevant in this setting. For example, the literature on diagnostic expectations suggests that exposure to positive cues leads individuals to form more optimistic expectations (Bordalo et al., 2024). Accordingly, favorable news about outside options could make bankers overly optimistic, adopt less cautious behavior, and engage in riskier lending practices. Our mechanism results in Section 6.2, however, suggest that more optimistic beliefs alone cannot explain our main findings. Finally, improved outside options may drive strategic behaviors beyond the scope of our model. For instance, bankers may leverage their enhanced bargaining power to negotiate *golden parachutes*, i.e., more generous severance packages, which lower the cost of dismissal and thereby encourage risk-taking. They may also bargain

for greater discretion over lending itself. These channels operate through bankers' strengthened position in the labor market and reinforce, rather than confound, the relationship we document.

## 3 Data

For our main analysis, we combine data on syndicated lending with employment histories of senior US investment bankers obtained from *Revelio Labs* as well as supplementary data sources on firm performance and wages. 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 an important factor for financial stability. With a median loan size in our sample of 400 million USD, decisions over these loan contracts constitute high-stakes choices. In 2018, the 2.8 trillion USD syndicated lending market exceeded the 1.3 trillion USD corporate bond market, highlighting its central role in financing US firms. Second, the risk associated with loan default is not contained within a single financial institution but disseminated throughout the financial sector via the syndication process itself as well as through trading and securitization in the secondary market (Mugasha, 2004). Finally, lending choices can be attributed to the arranging bank, with prior literature suggesting that individual lead bankers exert substantial influence over the design of these loans (Herpfer, 2021; Bushman et al., 2021).

**Dealscan:** Data on lending activity by banks are downloaded from *Dealscan*. From the universe of loans recorded in the database, we identify the 1500 largest lead arranging banks in terms of the number of loans issued and include all tranches arranged by these banks in our sample. For each loan, we include information on the borrowing and lending firm identity, tranche amount, and maturity, whether the loan is secured, and whether covenants are attached. Summary statistics on the tranche-level data are shown in Table A1. To measure credit quantity, we also aggregate the data to the lender-quarter level to obtain both 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.[5] 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.[6] Third, to identify senior bankers, we only retain spells with a seniority level at or above 4. Finally, we only retain full-time bankers by excluding overlapping spells. We use all employment spells between 1994 and 2020.[7] Panel A of Table A2 shows summary statistics for this sample. As expected, the sample predominantly consists of male, white, and highly educated employees with high incomes (annually around 150,000 USD on average). Due to the backfilled nature of the employment histories, the mean age of employees is relatively young, at 37 years. Table A3 compares key demographic variables between the LinkedIn dataset and administrative data sources. Qualitatively, the sample captures the key characteristics of individuals employed in the financial industry reported in the CPS and ACS.[8] These similarities are even more pronounced when the restriction on seniority is removed.

For our main analysis, we combine the lending data from Dealscan with an outside options proxy calculated from employment histories at the parent company level. To this end, we sequentially merge on exact co-occurrences of parent companies' GVKEY, ticker, and company names, which have been cleaned and normalized beforehand, retaining only unique merges. For unmatched observations, we repeat the procedure at the subsidiary level, linking parent companies through their subsidiaries when matches are identified. In cases where 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 are able to

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

[6] The included roles are: "Investment Specialist", "Investment Banking", "Banker", "Credit Specialist", "Financial Advisor", "Loan Officer", and "Financial Analyst".

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

[8] Both are obtained via IPUMS. For details on the ACS data, we refer to Ruggles et al. (2025).

merge 1268 parent companies, comprising two-thirds of subsidiaries in Dealscan. Among the 1000 largest lenders, this accounts for 99% of individual loans and 91% of total lending volume.

For a limited sample of loans, we are able to identify individual lead arranging bankers by name and affiliation and match them to their respective employment history in the employment history data. We follow Herpfer (2021) in extracting banker signatures from syndicated loan contracts contained in SEC filings and match these to their employment history using the combination of the name, affiliation, and date on the filing. Panel B of Table A2 shows summary statistics for this sample.

**Compustat:** We obtain data on firm-level fundamentals from Compustat. For both borrowing and lending firms, we include data on ratings, assets, liabilities, net income, EBIT, short-term debt, long-term debt, employees, shareholder equity, and capital expenditure, with summary statistics shown in Table A4. We also exploit borrower firm S&P credit ratings as a measure for credit risk and repayment probability. We use the linking tables by Chava and Roberts (2008) and Schwert (2020) to match Dealscan and Compustat borrower and lender firms (see Panels A and B of Table A3). To ensure a consistent sample of firms throughout the analysis, we only use data on banks for which we observe syndicated loan activity, employment histories, and balance sheet information.

**(Conditional) Value at Risk:** To measure financial risk, we use data from Adrian and Brunnermeier (2016), which are available at quarterly frequency between 1994 and 2009. The first measure is *Value at Risk* (VaR), which captures the maximum loss for an institution $i$ at the 95% or 99% confidence level, i.e., 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. In other words, CoVaR quantifies the expected loss to the financial system conditional on a $95^{\text{th}}$ or $99^{\text{th}}$ percentile loss at bank $i$, capturing the (non-causal) contribution of bank $i$ to systemic risk. Adrian and Brunnermeier (2016) estimate these measures using quantile regressions. Summary statistics are shown in Panel C of Table A3.

**BoardEx:** We use information on banker pay from BoardEx, a database provided by *Delinean*. These data include detailed information on compensation for top executives of large, listed companies in the United States since 1997. 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 executive oversight.[9] Summary statistics are shown in Panel D of Table A3.

**Investment Advisor Data:** We leverage data on misconduct among U.S. investment advisors, covering individuals registered with the Security and Exchange Commission's (SEC), a state authority, or both. The dataset is a panel spanning 2007 to 2015 and includes detailed employment histories alongside annual counts of disclosures related to misconduct or customer complaints. We combine this information with our measure of outside options at the parent company level, matching sequentially on CIK, web domain, and bank name. The final sample includes approximately 140,000 distinct individuals.[10]

# 4 Measuring Outside Options

This section describes our network-based measure of outside options, followed by a number of validation tests. We construct a measure that captures meaningful variation in outside options while remaining orthogonal to bank-level shocks. The identification approach exploits variation in labor demand at other institutions, transmitted to a bank's workers through their former coworkers, which is plausibly unrelated to the bank's current situation. 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). Our measure is built from LinkedIn data on employee job mobility, drawn from public profiles.

At its core, our outside options measure counts new 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. More formally, for bankers at a given bank $i$ in quarter $t$, our

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

[10] Egan, Matvos, and Seru construct the underlying data using publicly available records from the SEC's Investment Advisor Public Disclosure website. For additional details, we refer to Egan, Matvos, and Seru's homepage, Egan et al. (2019, 2022), as well as Egan et al. (2024) for a recent review of the literature.

measure of outside options is defined as follows:

$$InflowsAtTies_{it} = \sum_{j \neq i} w_{ijt} \times Inflows_{-i,jt} \tag{8}$$

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 from all other firms $k \neq i$ to firm $j$ in quarter $t$:

$$Inflows_{-i,jt} = \sum_{k \neq i} Transitions_{kjt}. \tag{9}$$

We exclude transitions from firm $i$ to $j$ in $t$ from our calculation in order to ensure orthogonality between our outside options measure and any bank-level dynamics in bank $i$ over time.

The weights measure the share of former coworkers now employed at a given bank. 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 to all other banks:

$$w_{ijt} = \frac{\sum_{h=4}^{12} Transitions_{ij,t-h}}{\sum_{m \neq i} \sum_{h=4}^{12} Transitions_{im,t-h}}. \tag{10}$$

The weights thus capture the social ties a bank's workers have to other firms, and hence their exposure to hiring at those firms.[11] In our baseline specification, we focus on ties that are between 4 and 12 quarters old. We limit the tie duration to 3 years, given that the median spell length in our sample is at around 13 quarters. We also include ties only one year after the transition to ensure that outflows from a firm do not contemporaneously affect the tie weight component of our measure. A bank's contemporaneous outflows therefore enter neither the labor-demand nor the tie-weight component of the measure. We demonstrate the robustness of our main results to alternative 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

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

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 industry (Fracassi et al., 2016; Jiang et al., 2018). In many cases, senior positions remain unadvertised, increasing banks' reliance 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. Workers 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 (e.g. as 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 caution against relying solely on spatial variation, 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 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.[12] 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 A2, the outside options measure exhibits a procyclical pattern over time, closely co-moving with the credit-to-GDP ratio and the number of employees in credit intermediation.

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 relation-

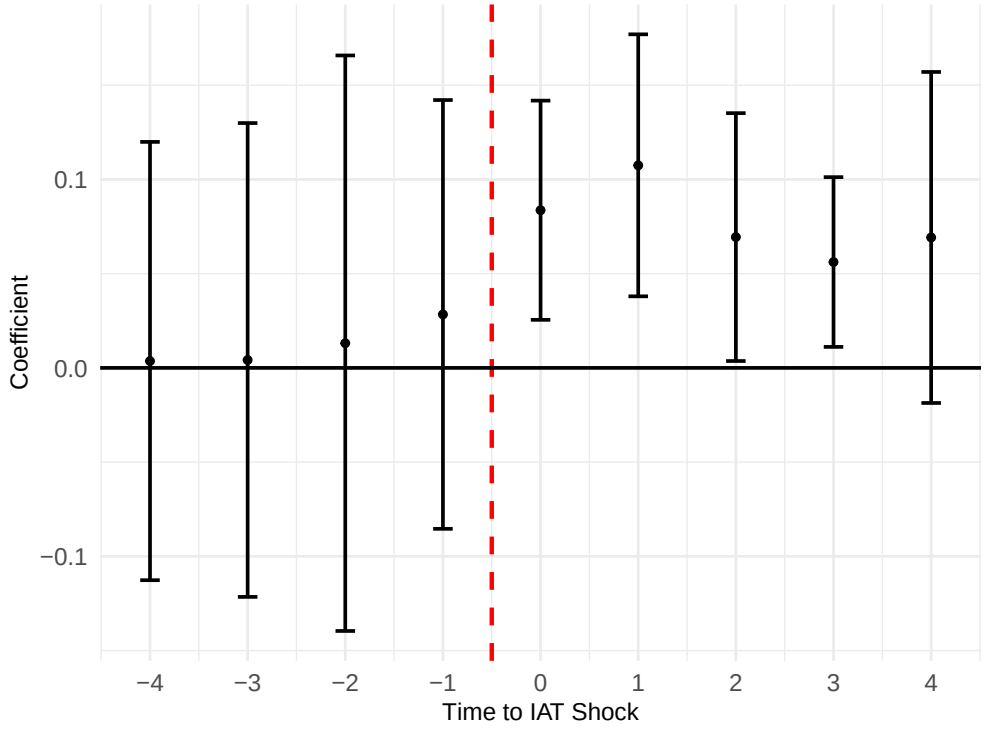
[12] We refer to Table A5 for summary statistics.

ship between outside options and employee mobility, we regress employee outflows from a given institution to other banks in our sample on our proxy for outside options, including bank and year-quarter fixed effects. We estimate separate models for each lead and lag of the outside options measure. The results, presented in Figure 1, show that outside options significantly increase employee outflows both on impact and in subsequent periods. This persistence is consistent with news shocks shifting beliefs and influencing search behavior over the medium term. Importantly, the coefficients on the leads are insignificant, indicating that elevated past outflows do not predict our outside options proxy. In Figure A3, we replicate the analysis using all employee outflows as the dependent variable, with results closely mirroring those in Figure 1. The pattern also remains unchanged for alternative timing assumptions for the construction of $InflowsAtTies_{it}$ (Figure A4).

Second, we examine whether better outside options translate into pay increases for employees who remain with their firms. To this end, we regress symmetric growth rates of firm-level compensation components on our outside options proxy, controlling for lender and year fixed effects. Table 1 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 pay components, bonuses and equity at risk, and find no significant response to variation in outside options. This contrast indicates that, conditional on controls, the proxy does not capture cyclical variation in banks' financial position, 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, confirming that our proxy reflects genuine variation in outside options.

In the main analysis, we regress loan-, banker-, and bank-level outcomes on our outside options measure. We can attribute a causal interpretation to the estimated coefficients if, conditional on covariates and fixed effects, unobserved determinants of lending behavior or bank risk are uncorrelated with variation in labor demand at connected banks. As a shift-share variable, $InflowsAtTies_{it}$ inherits the exogeneity conditions of such designs, where the shares are the tie weights $w_{ijt}$ and the shocks are labor demand $Inflows_{\_i,jt}$ at connected banks. While most of the literature exploits exogenous shares, we follow the exogenous-shifts approach (Borusyak et al.,

Figure 1: Effect of Outside Options on Outflows to Other Banking Roles




*Notes*: The figure shows coefficients from regressions of employee outflows to other banks in our sample on inflows at ties, using the Poisson estimator for dispersed count variables with meaningful zeros (Wooldridge, 1999). The coefficients come from separate regressions on a series of leads and lags of inflows at ties, all including lender and year-quarter fixed effects. The inflows at ties measure is standardized to a mean of zero and a standard deviation of one. The figure shows 95 percent confidence intervals calculated using two-way clustered standard errors at the lender and year-quarter level. Time is measured in quarters.

2025), which requires the shocks, but not the shares, to be as good as randomly assigned. This distinction is relevant to our setting, since a bank's network may be correlated with its characteristics while identification remains valid as long as the hiring shocks transmitted through it are not. Formally, two conditions have to be satisfied (Borusyak et al., 2022). First, the underlying shocks must be as-good-as-randomly assigned, without requiring exogeneity of the shares. Second, identification hinges on sufficient variation in the shocks, which arises when they are many and relatively independent, each affecting only a small number of units.

The first condition is plausibly met in our setting, as labor demand shocks at other institutions are, conditional on controls, unlikely to be correlated with unobservable factors that determine a bank's outcomes. As direct evidence, we regress inflows at ties on balance-sheet financials from Compustat and find that bank observables do not predict the measure. Conditional on fixed

Table 1: 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) | (0.029) | (0.123) | (0.123) | (0.094) | (0.096) |
| Lender fixed effects | X | X | X | X | X | X |
| Year-Quarter fixed effects | 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 symmetric 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 double-clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

effects, future inflows at ties are unrelated to a bank's financial position, both in levels (Table A6) and in growth rates (Table A7).

We similarly expect the second condition to hold. The transition matrix across banks is sparse and mobility between institutions is heterogeneous, generating substantial variation in exposure across banks. As shown in Table A5, the average bank is connected to 24 other institutions in a given quarter. This number drops by about half when adjusting for size heterogeneity or restricting the sample to connected banks with positive inflows. At the same time, the total number of connected banks with non-zero hiring stands at 367 and has increased substantially over time (Figure A5). Therefore, an average bank is only connected to 7% of all hiring institutions, implying that individual banks' shocks are unlikely to dominate the measure. Next, we examine the extent to which hiring at other banks can be predicted by characteristics of the bank of interest. To do so, we regress hiring at connected banks on various sets of fixed effects and inspect the resulting $R^2$, with results presented in Table A8. $\text{Bank}_i$ fixed effects account for only a small share of hiring variation at connected banks, and their marginal contribution becomes negligible once fixed effects for the connected firm are included. Moreover, even the most comprehensive specification leaves roughly one-third of the variation in hiring unexplained.

# 5 Main Results

In this section, we examine the effect of our outside options measure on credit supply. We document that improved outside options are associated with higher credit volumes and increased financial risk at the lender level, thereby contributing to elevated systemic risk. We then demonstrate that these aggregate patterns reflect a shift toward riskier borrowers.

## 5.1 Lender-Level Outcomes

We estimate the response of lender-level variables to variation in inflows at ties. As discussed in Section 2, improved outside options are expected to result in a credit expansion accompanied by increases in bank risk. To test this empirically, we use the following specification for a bank $i$ at year-quarter $t$:

$$y_{it} = \beta InflowsAtTies_{it} + \Gamma V_{it} + \alpha_i + \lambda_t + \epsilon_{it} \tag{11}$$

where $y_{it}$ is the outcome of interest and $V_{it}$ is a vector of time-varying controls, comprising 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 terms $\alpha_i$ and $\lambda_t$ are fixed effects at the bank and year-quarter level. Standard errors are double-clustered at the lender and year-quarter level.

We assess the effects of outside options on lending volumes constructed from the syndicated loan data, with results presented in Table 2. In Columns (1) and (2), we estimate the effect of inflows at ties on loan volume growth. In line with our prediction, the estimated coefficients are positive and significant, both with and without time-varying lender controls. Quantitatively, a one standard deviation increase in outside options corresponds to a 1.9 percentage point rise in loan volume growth. To further dissect this effect, we distinguish between extensive and intensive margin responses. Columns (3) and (4) show that the likelihood of a bank serving as lead arranger rises when outside options improve, with an average marginal effect of 2.8 percentage points in our preferred specification in Column (4). In contrast, the coefficients on loan size, conditional on issuing any loan, are small and statistically insignificant. The volume response thus operates

Table 2: Effect of Outside Options on Lending Volumes

| | Growth Rate | | Extensive Margin | | Log Volume | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | OLS | OLS | Logit | Logit | OLS | OLS |
| IAT | 1.88* | 1.90* | 0.226* | 0.243** | 0.010 | 0.007 |
| | (1.01) | (1.02) | (0.119) | (0.119) | (0.028) | (0.027) |
| Lender fixed effects | X | X | X | X | X | X |
| Year-Quarter fixed effects | X | X | X | X | X | X |
| Lender Controls | | X | | X | | X |
| Observations | 6,277 | 6,277 | 3,999 | 3,999 | 4,058 | 4,058 |

*Notes*: The table reports results from regressing the outcome of interest on $InflowsAtTies_{it}$, lender controls, and fixed effects at the lender and year-quarter level. The outcome variables are symmetric growth rates of total lending volume in percentage points (Columns 1 and 2), an indicator equal to one if a bank arranged any loan (Columns 3 and 4), and the natural logarithm of the loan amount, conditional on lending a strictly positive amount (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. Columns (1), (2), (5), and (6) are estimated via OLS, while Columns (3) and (4) are obtained from logit regressions. Standard errors are double-clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

through banks arranging more loans rather than larger ones. As shown in Tables A9 and A10, our results are robust to varying both the activation lag and the duration for which ties remain active.

Next, we examine the effect of bankers' outside options on financial risk at the lending bank and its implications for systemic risk. Because credit risk accounts for a substantial share of the variation in banks' return characteristics (Begenau et al., 2025), riskier lending translates into elevated risk at the bank level. To measure financial risk, we draw on the metrics for both types of risk developed in Adrian and Brunnermeier (2016). Financial risk for a bank in isolation is captured by *Value at Risk* (VaR), defined as the maximum loss to bank $i$ at a given confidence level. A bank's contribution to systemic risk is measured by CoVaR, defined as the change in the VaR of the financial sector conditional on a corresponding percentile loss to bank $i$. In other words, CoVaR reflects the non-causal contribution of a bank to systemic risk. We use the estimates provided by Adrian and Brunnermeier (2016) at the 95% and 99% confidence levels, transformed into symmetric growth rates, and re-estimate Equation (11).

The results are reported in Table 3. Columns (1) to (4) present the estimates for VaR and CoVaR at the 95% confidence level, where the coefficients are positive but statistically insignificant. In Columns (5) to (8), we shift focus to more extreme levels of financial distress by using VaR and

Table 3: Effect of Outside Options on Changes in Financial Risk (in Percentage Points)

| | VaR 95% | | CoVaR 95% | | VaR 99% | | CoVaR 99% | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| IAT | 0.247 | 0.246 | 0.190 | 0.187 | 0.452*** | 0.447*** | 0.408*** | 0.401*** |
| | (0.254) | (0.253) | (0.195) | (0.192) | (0.162) | (0.161) | (0.129) | (0.126) |
| Lender fixed effects | X | X | X | X | X | X | X | X |
| Year-Quarter fixed effects | X | X | X | X | X | X | X | X |
| Lender Controls | | X | | X | | X | | X |
| Observations | 10,635 | 10,635 | 10,635 | 10,635 | 10,635 | 10,635 | 10,635 | 10,635 |

*Notes*: The table reports coefficients from OLS regressions of symmetric growth rates in VaR and CoVaR (in percentage points) on $InflowsAtTies_{it}$, lender controls, and fixed effects at the lender and year-quarter level. The outcomes are VaR (Columns 1, 2, 5 and 6) and CoVaR (Columns 3, 4, 7 and 8), computed at the 95% confidence level (Columns 1 to 4) and the 99% confidence level (Columns 5 to 8). 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 double-clustered at the lender and year-quarter level. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

CoVaR at the 99% confidence level as outcomes. The estimated coefficients roughly double in magnitude and become significant at the 1% level. A one standard deviation improvement in outside options is associated with increases in VaR and CoVaR of approximately 0.45 and 0.40 percentage points, respectively. This pattern suggests that the additional risk is concentrated in the tail of the loss distribution, where the implications for financial stability are greatest. Results for alternative tie lengths, reported in Tables A11 and A12, provide support for these conclusions.

Crucially, these effects are not confined to the originating bank under scrutiny but extend to the broader financial system, pointing to systemic implications of bankers' labor market conditions. To gauge the magnitude of the estimates, consider that between 2003 and 2008 outside options rose by more than two standard deviations, while CoVaR increased by approximately 52%. A back-of-the-envelope calculation, extrapolating our marginal estimate over this range, attributes around 1.8% of the rise in systemic risk to changes in outside options. The channel is thus economically meaningful.

### 5.2 Borrower Risk

We scrutinize the loan-level dynamics underlying these bank-level patterns. Consider a bank $i$ issuing a loan $l$ to borrower $b$ in year-quarter $t$. The loan-level specification is given by:

$$y_{bt} = \beta \, InflowsAtTies_{it} + \Gamma V_{it} + \Theta W_{bt} + \Pi Z_l + \alpha_i + \lambda_t + \epsilon_{iblt}, \tag{12}$$

where $y_{bt}$ 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 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 $Z_l$, comprising the inverse hyperbolic sine of tranche amount and maturity and indicators for whether the loan is secured and whether covenants are attached.

The results are presented in Table 4. In Columns (1) to (3), the outcome is a borrower-level indicator for an investment-grade rating by S&P, while in Columns (4) to (6), it is an ordinal credit rating normalized to range between 0 and 1. The specifications in Columns (1) and (4) mirror those at the bank level, and the estimated coefficients are negative but statistically insignificant. Once we include borrower controls in Columns (2) and (5), the coefficients increase in absolute magnitude and become highly significant, while controlling for loan-level characteristics in Columns (3) and (6) does not substantially alter the estimates. The borrower controls capture firm size, which is in turn correlated with investment-grade status (Table A13). In the absence of these controls, the coefficient masks two offsetting effects: a shift toward larger firms and, conditional on firm size, toward riskier ones. Controlling for size isolates the latter effect, which is quantitatively meaningful. A one standard deviation increase in outside options reduces the share of investment-grade borrowers by 1.7% of its mean. Together with the bank-level results, this points to a credit expansion accompanied by a deterioration in borrower quality.

We perform a series of robustness checks for our main result in Column (3), reported in Table A14. First, the coefficient of interest remains stable when we include leads and lags of inflows at ties. The estimated coefficients also remain significant and comparable in magnitude when accounting for time-varying demand-side factors (Huang et al., 2024, 2025) by adding fixed effects for borrowers' SIC sectors and states, each interacted with year-quarters. Similarly, our baseline

Table 4: Effect of Outside Options on Borrower Risk

| | Borrower Prime | | | Borrower Rating | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| IAT | -0.002 | -0.005*** | -0.005*** | -0.0001 | -0.002** | -0.002** |
| | (0.001) | (0.001) | (0.001) | (0.0010) | (0.0007) | (0.0007) |
| Lender fixed effects | X | X | X | X | X | X |
| Year-Quarter fixed effects | X | X | X | X | X | X |
| Lender Controls | X | X | X | X | X | X |
| Borrower Controls | | X | X | | X | X |
| Loan Controls | | | X | | | X |
| Outcome Mean | 0.296 | 0.296 | 0.296 | 0.462 | 0.462 | 0.462 |
| Observations | 55,327 | 55,327 | 55,327 | 55,327 | 55,327 | 55,327 |

*Notes*: The table reports results from estimating Equation (12) at the loan level. The dependent variables are an indicator for investment-grade borrowers (Columns 1 to 3) and an ordinal borrower rating normalized to range between 0 and 1 (Columns 4 to 6). The independent variable is $InflowsAtTies_{it}$. Borrower and lender controls include the inverse hyperbolic sine transformation of total assets, number of employees, capital expenditure, total liabilities, EBIT, and (for borrowers) fixed assets. Loan controls are the inverse hyperbolic sine transformation of tranche amount and maturity and indicators for whether the loan is secured and whether covenants are attached. All regressions include fixed effects at the lender and year-quarter level, and standard errors are double-clustered at the same levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

findings are robust to using only within-lender-year variation, as well as to controlling for outflows or the number of lenders. The results also continue to hold when we restrict the sample to post-2008 loans or to newly originated loans. Lastly, we show that our main results are robust to alternative assumptions about the duration for which ties remain active (Tables A15 and A16).

A first-order question is whether this shift reflects a genuine increase in risk-taking rather than yield-seeking behavior. In case of the latter, 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 same controls and fixed effects as in the baseline. As reported in Table A17, the estimated coefficients are small and statistically insignificant, allowing us to rule out spread increases larger than roughly four basis points per standard-deviation shock, which amounts to about 1% of the outcome mean, at the 95% confidence level. Banks thus take on riskier borrowers without demanding significantly higher compensation, which is difficult to reconcile with yield-seeking.

Another concern is that stronger ties between institutions may also increase the flow of information about a banker's current on-the-job behavior to other employers. Former colleagues

or individuals who have interacted with the banker may be better positioned to assess their performance and provide hiring recommendations. One might therefore worry that bankers behave more cautiously when well-connected firms are hiring, as these firms are better able to observe current risk-taking. From a theoretical standpoint, however, such an effect should make bankers more cautious, meaning the information flow channel would counteract our main mechanism. As a result, any bias would attenuate our estimated coefficients toward zero. We test the channel directly by leveraging the syndication process, through which banks become linked via repeated co-arrangement of loans. We construct a variant of our measure in which ties are based on syndication links rather than coworker networks, capturing inter-bank information flow without the labor-mobility content. Including both measures in Column (7) of Table A14 leaves the coefficient of interest unaffected, indicating that information flows on the employers' side do not drive our results.

We provide more direct evidence for our main mechanism by investigating whether the response of borrower ratings to outside options depends on the ease of job-to-job transitions. We focus on changes in the enforceability of non-compete agreements (NCAs), which restrict employees' ability to work for direct competitors in the same region and have been shown to diminish worker mobility and wages (Johnson et al., 2025). Crucially, their enforceability varies at the state level and is shifted by state court decisions that clarify or overturn precedent, providing plausibly exogenous variation in labor mobility. When enforceability decreases in the state where a bank is headquartered, its bankers become less constrained in exercising their outside options. We therefore expect the effect of outside options on borrower risk to be stronger following such decreases, and conversely weaker following increases. To test this, we interact our measure with the state-level NCA enforceability index of Mueller (2023), assigning each bank to its headquarters state and including state-year fixed effects to absorb time-varying geographic heterogeneity. The results in Table A18 are broadly in line with this prediction. The interaction of inflows at ties with past decreases in enforceability (Column 3) is negative and highly significant, indicating that states moving toward weaker enforceability drive the effect. By contrast, the interactions for increases in enforceability and a combined measure are insignificant.

The estimated coefficients reported in this section are moderate in magnitude but can be considered lower-bound estimates for several reasons. First, by estimating effects at the bank level,

we average across all investment bankers including those that are unresponsive to outside options, whether owing to 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 likely the component to which bankers respond most.[13] Third, our measure does not capture news about labor demand at other firms that is transmitted outside of personal networks, such as public job postings, positions at non-connected banks, or opportunities outside the financial industry. Taken together, our results reflect the average response to variation in one, plausibly exogenous component of outside options.

# 6 Mechanism

So far, we have provided evidence that better outside options increase bank risk by inducing a credit expansion toward riskier borrowers. To assess whether the insurance mechanism introduced in Section 2 can account for these effects, we turn to individual-level data. We present several pieces of evidence that, taken together, are difficult to reconcile with alternative explanations, such as behavioral factors (Cohn et al., 2015; Bordalo et al., 2018; Cohn et al., 2014) or residual demand-side forces, as the primary drivers of our results. Specifically, we show that individuals more exposed to dismissal risk respond more strongly to variation in outside options. We also document that outside options lead to behavior that harms both employers and clients, and reduce banks' ability to discipline employees for misconduct, consistent with the implicit insurance channel.

## 6.1 Banker-Level Heterogeneity

We assess banker-level heterogeneity in how outside options affect borrower risk, focusing on age for two key reasons. First, age can be reasonably inferred from employment history data. Second, and more importantly, age has a theoretically meaningful interpretation in the context of risk choices and outside options. The classical argument of career concerns suggests that such considerations discourage risky or shirking behavior, as employees have an incentive to signal

[13] Year-quarter fixed effects explain around 39% of the overall variation in inflows at ties, which further increases to 47% once controlling for bank fixed effects.

desirable traits to employers. Under this framework, labor markets serve as a disciplining device and mitigate agency problems within firms (Shapiro and Stiglitz, 1984; Holmström, 1999).

In our case, however, the differential response to variation in outside options across age groups is theoretically ambiguous. On one hand, because improvements in outside options reduce the cost of job loss, younger individuals should be more responsive to the implicit insurance they provide and make riskier choices, as illustrated in Section 2. On the other hand, younger individuals also have a longer remaining career over which reputational damage can compound. If outside-option improvements are perceived as persistent, or if excessive risk-taking inflicts lasting reputational harm, these career-long consequences could outweigh the insurance benefit and make younger bankers more cautious instead.

To take these considerations to the data, we extend Equation (12) by interacting banker age with inflows at ties, using our sample of loans matched to individual bankers. All regressions include banker fixed effects, which, together with the other fixed effects, absorb the standalone coefficient on age. The results, presented in Table 5, show that outside options are consistently negatively associated with the likelihood of lending to prime-rated borrowers, while the interaction with age is large, positive, and highly significant. Despite the small sample size, this pattern holds across Columns (1) to (3), which replicate the specifications in Table 4, and continues to hold under more granular fixed effects. Column (4) adds lender-year-quarter fixed effects, which absorb the standalone coefficient on inflows at ties, and Column (5) further includes metro-area-year-quarter fixed effects in order to eliminate time-varying local economic conditions.

A further concern is that bankers' labor market mobility is partly driven by lift-outs, whereby senior bankers are poached and take their entire team with them. Such a pattern would, if anything, imply stronger effects among senior bankers. The age interaction instead places the effect among younger bankers. We also address this concern directly in Column (6) by interacting lender-year-quarter fixed effects with metro areas, thus relying only on variation within the same lender across space and leaving the estimate essentially unchanged. Finally, Column (7) interacts inflows at ties with spell-level controls, namely seniority, position number, job tenure, and imputed salary, and the age interaction remains stable. Tables A19 and A20 report the equivalent regressions with continuous rating and tranche amounts as outcomes, with consistent results.

Table 5: Effect of Outside Options on Borrower Prime Rating: Age Heterogeneity

| | Borrower Prime Rating | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| IAT | -0.587*** | -0.495** | -0.482** | | | | |
| | (0.179) | (0.189) | (0.200) | | | | |
| IAT × Age | 0.010** | 0.009*** | 0.009** | 0.012*** | 0.012*** | 0.012*** | 0.012** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.004) |
| Lender fixed effects | X | X | X | | | | |
| Year-Quarter fixed effects | X | X | X | | | | |
| Banker fixed effects | X | X | X | X | X | X | X |
| Lender × Year-Quarter fixed effects | | | | X | X | | X |
| MSA × Year-Quarter fixed effects | | | | | X | | X |
| Lender × MSA × Year-Quarter fixed effects | | | | | | X | |
| Lender Controls | X | X | X | | | | |
| Borrower Controls | | X | X | X | X | X | X |
| Loan Controls | | | X | X | X | X | X |
| IAT × Spell Controls | | | | | | | X |
| Outcome Mean | 0.153 | 0.153 | 0.085 | 0.174 | 0.174 | 0.174 | 0.208 |
| Observations | 275 | 275 | 275 | 327 | 327 | 327 | 327 |

*Notes*: The table reports results from estimating Equation (12) at the loan level. The dependent variable is an indicator for investment-grade borrowers. The independent variables are $InflowsAtTies_{it}$ and its interaction with the banker's age. Borrower and lender controls include the inverse hyperbolic sine transformation of total assets, number of employees, capital expenditure, total liabilities, EBIT, and (for borrowers) fixed assets. Loan controls are the inverse hyperbolic sine transformation of tranche amount and maturity, and indicators for whether the loan is secured, and whether covenants are attached. *Spell controls* contains the position number, the seniority level, the inverse hyperbolic sine transformation of imputed salary and job tenure, each included interacted with $InflowsAtTies_{it}$ and (if possible) as a standalone variable. Standard errors are double-clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

For all outcomes, the coefficients on the interaction with age are of the opposite sign as the corresponding baseline coefficient, implying that the effects of outside options on lending are concentrated among younger employees. This is consistent with the idea that outside options act as insurance against downside risk. Typically, less experienced bankers have accumulated less firm-specific capital and smaller internal networks, making them more dependent on outside labor market conditions. Similarly, younger individuals may face tighter financial constraints in their private consumption decisions.

## 6.2 Evidence on Advisor Misconduct

Since our results suggest that better outside options lead to riskier behavior, this effect should manifest beyond the domain of loan officers' decisions. We turn to the market for investment advisors for three reasons. First, misconduct provides clear instances of wrongdoing, cases in which employees acted against their employer's interest. Credit decisions offer no such indication,

since the optimal level of risk-taking is ex-ante unclear. The advisor setting is therefore a cleaner test of whether outside options induce harmful behavior. Second, as disclosures of misconduct are publicly available, the setting allows us to examine how such behavior affects labor market outcomes. Finally, the results generalize our main finding on the effect of outside options on workers' job-related choices beyond the narrow corporate banker market to the workforce in the financial industry more broadly. In doing so, 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 study how variation in outside options influences the frequency of advisor misconduct, building on Equation (12). We aggregate inflows at ties to the annual frequency and focus on the first lag of the measure, as misconduct typically takes time to be discovered and disclosed. Our analysis considers three outcome variables: the number of misconduct disclosures an advisor receives in a given year, the number of customer complaints filed against them, 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 6. Across the board, better outside options correspond to large and significant increases in overall misconduct, customer complaints, and settlements, respectively. For each of these outcomes, this holds conditional on the baseline fixed effects and additional lender-advisor fixed effects. In Tables A21, A22, and A23, we provide a battery of robustness checks for these results. The findings remain unaffected by augmenting the regressions with state-year fixed effects, including the contemporaneous levels and the second lag of inflows at ties, controlling for lagged outflows, and binarizing the outcome variable. Quantitatively, these effects are sizeable, as a one standard deviation improvement in outside options maps into an increase in misconduct disclosures of roughly 30%. The associated costs to the financial sector are substantial. With average settlement costs of 550,000 USD per case (Egan et al., 2019), a one 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 firms tend to punish misconduct among investment advisors. Employment separations become much more likely following related disclosures, even though the broader market partly offsets this penalty through rehiring. Our mechanism posits that out-

Table 6: 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*** |
| | (0.0009) | (0.0008) | (0.002) | (0.001) | (0.001) | (0.0010) |
| Lender fixed effects | X | | X | | X | |
| Year fixed effects | X | X | X | X | X | X |
| Lender × Advisor fixed effects | | X | | X | | X |
| Lender Controls | X | X | X | X | X | X |
| Outcome Mean | 0.010 | 0.009 | 0.018 | 0.017 | 0.008 | 0.008 |
| Observations | 582,568 | 551,079 | 582,568 | 551,079 | 582,568 | 551,079 |

*Notes*: The table reports results from estimating Equation (12) at annual frequency at the advisor level. The dependent variables are the numbers 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 (Column 5 and 6). The main independent variable is $InflowsAtTies_{it}$. 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 are estimated with year fixed effects and lender controls, with the latter replaced by lender-advisor fixed effects in Columns (2), (4), and (6). Standard errors are clustered at the lender level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

side options insure workers against adverse outcomes by lowering both the likelihood and the cost of separation, reducing the deterrent effect of job loss following misconduct. A banker who anticipates this insurance and takes more risk responds rationally to weakened incentives, which distinguishes our mechanism from purely behavioral explanations such as overoptimism.

We test this conjecture by estimating the differential effect of misconduct on three distinct outcomes, comparing individuals with better versus worse outside options. Specifically, for an advisor $a$ employed at bank $i$ in year $t$, we define the following indicators for transitions between year $t$ and $t+1$: (*i*) $\text{Separation}_{at}$, equal to one if the advisor is no longer employed at $i$; (*ii*) $\text{IndustryExit}_{at}$, equal to one if the advisor is no longer recorded in the sample, which we define as exiting the industry; and (*iii*) $\text{Reemployment}_{at}$, equal to 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 $\text{Separation}_{at}$ and $\text{IndustryExit}_{at}$. Second, conditional on experiencing a job separation, we estimate the differential effects on $\text{IndustryExit}_{at}$ and $\text{Reemployment}_{at}$.

For the unconditional effects, consider the following specification:

$$y_{at} = \beta_1 Misconduct_{at} + \beta_2 Misconduct_{at} \times InflowsAtTies_{it} + \beta_3 Misconduct_{at} \times InflowsAtTies_{it-1} + \Gamma V_{it} + \alpha_{ai} + \lambda_{it} + \epsilon_{ait}, \quad (13)$$

that is, we regress an outcome $y_{at}$ on an indicator for misconduct, alone and interacted with contemporaneous values and the first lag of inflows at ties. We include fixed effects at the lender-year level, removing the baseline coefficient on outside options, and at the advisor or lender-advisor level. For the conditional effects, we further augment this setup by including all potential interactions with $\text{Separation}_{at}$, focusing on $\text{IndustryExit}_{at}$ and $\text{Reemployment}_{at}$ as outcome variables.

The results are reported in Table 7. While we are particularly interested in the interactions with lagged outside options, we control for contemporaneous inflows at ties and all potential interactions in all regressions. In Columns (1) and (2), we estimate the unconditional specification for the probability of a job separation, including advisor and lender-advisor fixed effects, respectively. As expected, misconduct enters with a large, positive, and highly significant coefficient, corroborating the results of Egan et al. (2019). However, the estimated coefficient on the interaction with lagged inflows at ties is negative, highly significant, and sizeable: the probability of job separation following misconduct is reduced by around 22% when inflows at ties are one standard deviation above the mean. Thus, better outside options lower the probability of experiencing a job separation following a misconduct disclosure, providing evidence of employers' reduced disciplining power.

In Columns (3) and (4), we repeat the estimation using $\text{IndustryExit}_{at}$ as the outcome. Again, better outside options counteract the main effect, reducing the probability of leaving the industry following a misconduct disclosure. This pattern could be driven by both changes in job separations and hiring at other firms. To isolate the latter change, we re-estimate Equation (13) and interact the variables of interest with $\text{Separation}_{at}$. The results, included in Columns (5) and (6), point to an important role for hiring. As before, misconduct-related separations raise the probability of exiting the industry, but this effect is muted for individuals with above-average outside options. Lastly, we find very similar results for $\text{Reemployment}_{at}$, an indicator for working at a

Table 7: Effect of Outside Options on Labor Market Disciplining

| | Job Separation | | | Leave Industry | | | Reemployment Next Year | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Misconduct | 0.425*** | 0.443*** | 0.237*** | 0.239*** | 0.004 | 0.003 | -0.006 | -0.004 |
| | (0.052) | (0.050) | (0.029) | (0.029) | (0.009) | (0.007) | (0.011) | (0.010) |
| Misconduct × $IAT_t$ | 0.015 | 0.018 | 0.018 | 0.018 | -0.0001 | -0.0006 | 0.002 | 0.003 |
| | (0.025) | (0.022) | (0.017) | (0.016) | (0.004) | (0.003) | (0.004) | (0.003) |
| Misconduct × $IAT_{t-1}$ | -0.075*** | -0.086*** | -0.054*** | -0.055*** | 0.001 | 0.002 | -0.002 | -0.003 |
| | (0.023) | (0.019) | (0.013) | (0.013) | (0.004) | (0.004) | (0.005) | (0.005) |
| Job Separation × Misconduct | | | | | 0.133** | 0.127* | -0.140** | -0.127* |
| | | | | | (0.058) | (0.063) | (0.068) | (0.072) |
| Job Separation × $IAT_t$ | | | | | -0.015 | 0.002 | 0.028* | 0.014 |
| | | | | | (0.016) | (0.017) | (0.016) | (0.015) |
| Job Separation × $IAT_{t-1}$ | | | | | -0.040*** | -0.033*** | 0.032*** | 0.022** |
| | | | | | (0.008) | (0.007) | (0.010) | (0.009) |
| Job Separation × Misconduct × $IAT_t$ | | | | | 0.053* | 0.043 | -0.057 | -0.051 |
| | | | | | (0.027) | (0.029) | (0.035) | (0.035) |
| Job Separation × Misconduct × $IAT_{t-1}$ | | | | | -0.068*** | -0.061*** | 0.077*** | 0.072*** |
| | | | | | (0.015) | (0.021) | (0.020) | (0.025) |
| 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 |
| Lender Controls | | | | | | | | |
| Outcome Mean | 0.119 | 0.109 | 0.038 | 0.037 | 0.038 | 0.037 | 0.079 | 0.071 |
| Observations | 598,839 | 589,763 | 598,839 | 589,763 | 598,839 | 589,763 | 598,839 | 589,763 |

*Notes*: The table reports results from estimating versions of Equation (13) at annual frequency at the advisor level. The dependent variables are an indicator equal to one if the advisor is no longer employed at $i$ in year $t+1$ (Columns 1 and 2), an indicator equal to one if the advisor is no longer recorded in the sample (Columns 3 to 6), and an indicator equal to one if the advisor is employed at another firm in the sample in $t+1$ (Columns 7 and 8). The main independent variables are $InflowsAtTies_{it}$, $InflowsAtTies_{it-1}$ and an indicator for having a misconduct disclosure in year $t$. The specification is given by Equation (13) in Columns (1) to (4), with all variables interacted with the indicator for job separations in Columns (5) to (8). All models include fixed effects at the lender-year and at the advisor (Columns 1, 3, 5, and 7) or lender-advisor level (Columns 2, 4, 6, and 8). Standard errors are clustered at the lender level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

different employer within the financial sector in the following year, reported in Columns (7) and (8).

Taken together, these results suggest that outside options reduce the probability of separation following misconduct and, even conditional on separation, make reemployment more likely. Outside options thus reduce the downside of risky behavior, thereby offsetting part of the disciplining role of labor markets.

# 7 Conclusion

This paper documents that better labor market outside options for bankers lead to riskier lending behavior and contribute to fluctuations in systemic risk. Using transaction-level data on syndicated loans, we find that banks exposed to improved outside options expand lending volumes

by shifting toward riskier borrowers, increasing financial risk at both the bank and system levels. We argue that these effects arise because stronger outside options provide implicit insurance against adverse outcomes, weakening the disciplinary role of dismissal risk and amplifying credit cycles. We show that these patterns persist in a related setting, the market for financial advisors, where better outside options raise misconduct and attenuate the labor market penalties of such violations.

These findings have implications for market participants and policymakers alike. Our results suggest that variation in sectoral labor market conditions affects the strength of employer disciplining power, with consequences for operational risk and settlement costs. During hot labor markets, banks may thus benefit from strengthening incentive alignment to limit the scope for adverse on-the-job behavior, for instance by increasing the use of deferred compensation and claw-back provisions as well as by setting stricter risk limits. Yet an individual bank's ability to do so may be limited. The disciplinary value of these tools erodes when outside options improve, since better options shorten expected tenure, and a bank that defers compensation more aggressively becomes less attractive to talent when rivals are hiring.

The results also have implications for the design of macroprudential policy. The mechanism we document operates through a labor market externality that individual banks do not internalize and cannot offset in isolation, since deferring compensation unilaterally reduces a bank's ability to retain talent. This points to a potential role for coordination. Minimum sector-wide standards on the horizon of compensation, implemented through deferred pay and clawback provisions, could therefore help address the externality at the level at which it arises.

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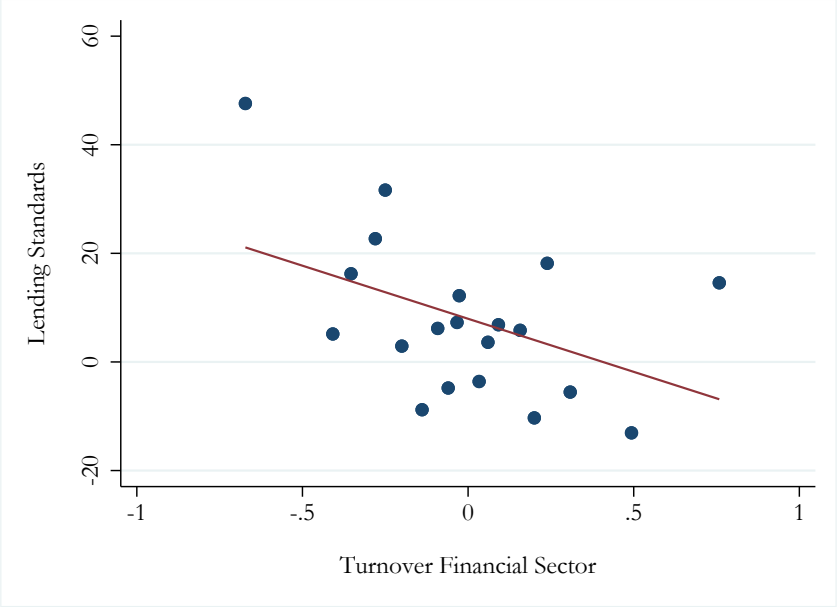
# A Additional Figures

Figure A1: Labor Market Turnover in the Financial Sector and Variation in Credit Standards

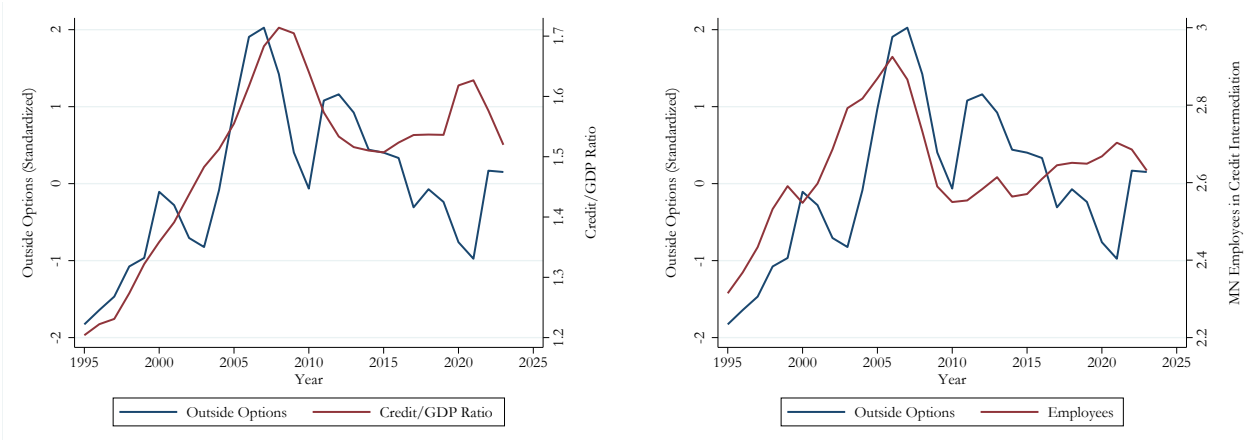



*Notes*: The figure binscatters voluntary labor market turnover in the financial sector against variation in lending standards. Labor market turnover is defined as the sum of hiring and quit rates in financial activities (FRED series JTU510099HIL and JTU510099QUR), which we transform into first differences. Lending standards are measured as the net percentage of domestic banks tightening their standards across loan categories, which is calculated based on data from Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS) and weighted by banks' outstanding loan balances (FRED series SUBLPDMOSXWBNQ).

Figure A2: Procyclicality of Inflows at Ties

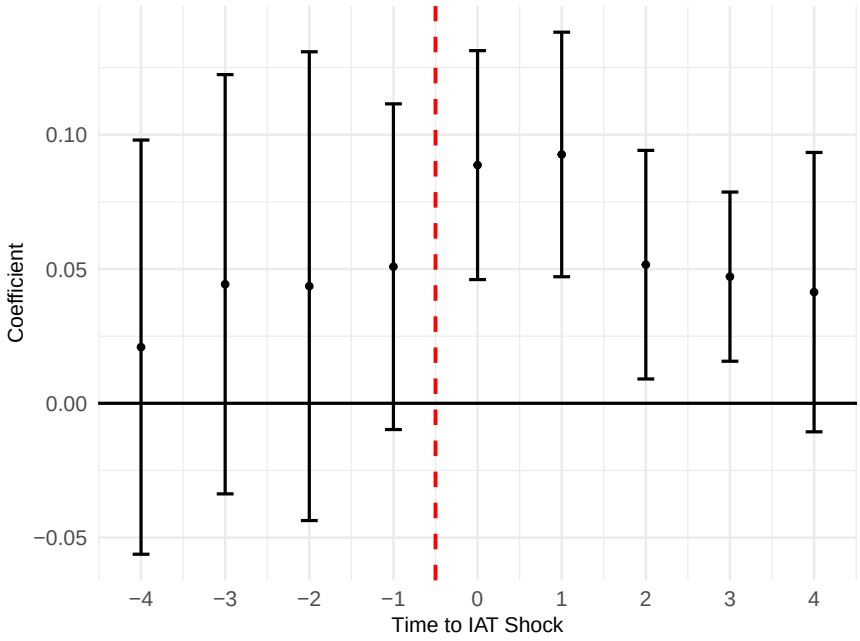
(a) Credit/GDP

(b) Employment in Credit Intermediation




*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). The aggregate data are obtained via FRED (series: QUSPAM770A and CEU5552200001).

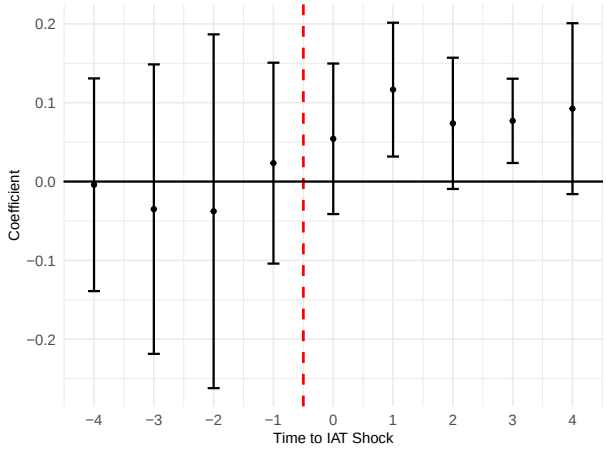
Figure A3: Effect of Outside Options on All Outflows



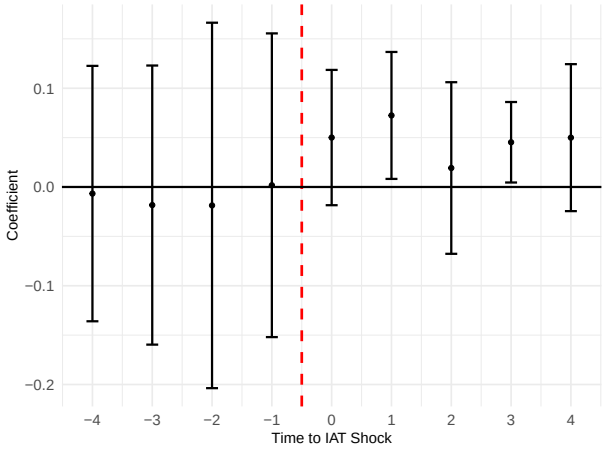

*Notes*: The figure shows coefficients from regressions of all employee outflows on inflows at ties, using the Poisson estimator for dispersed count variables with meaningful zeros (Wooldridge, 1999). The coefficients come from separate models on a series of leads and lags of inflows at ties. The inflows at ties measure is standardized to a mean of zero and a standard deviation of one. The figure shows 95 percent confidence intervals calculated using two-way clustered standard errors at the lender and year-quarter level.

Figure A4: Effect of Outside Options on Outflows—Robustness to Alternative Tie Lengths

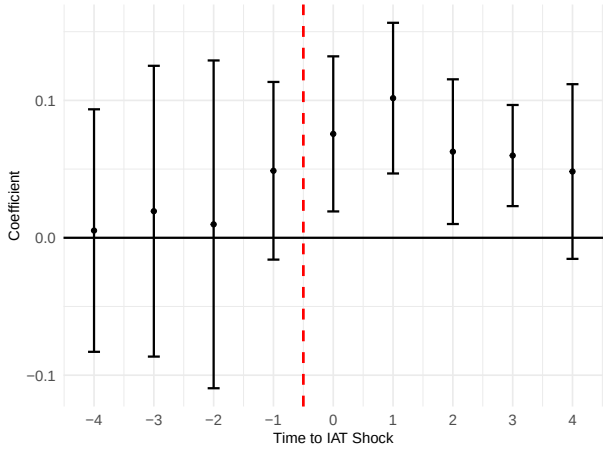
(a) Banking Roles, Ties Active 2-12 Quarters



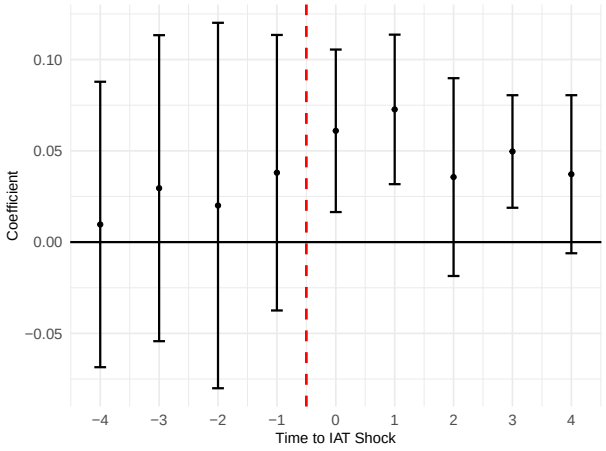

(b) Banking Roles, Ties Active 4-20 Quarters




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

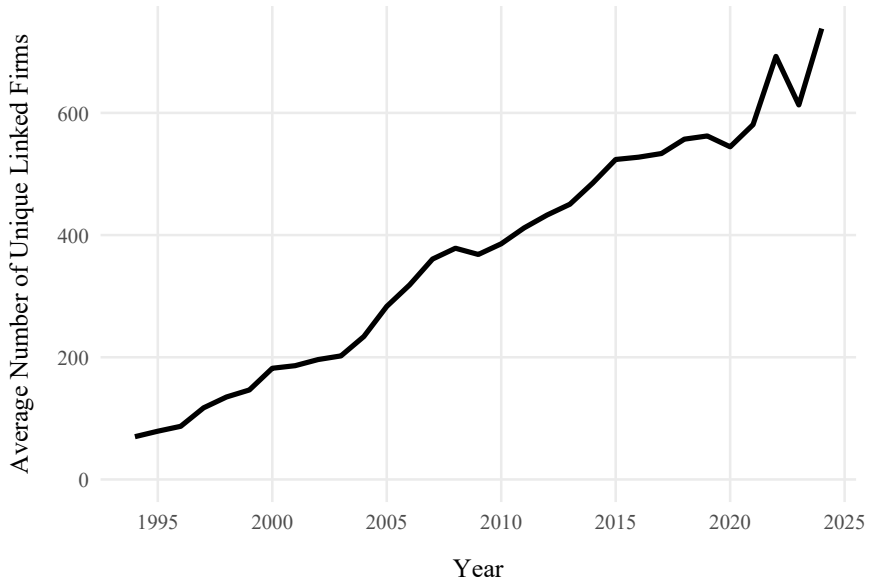



(d) All Roles, Ties Active 4-20 Quarters




*Notes*: The figure shows coefficients from regressions of employee outflows on inflows at ties calculated under alternative timing assumptions, using the Poisson estimator for dispersed count variables with meaningful zeros (Wooldridge, 1999). The dependent variables are outflows to other banking roles (Panels a and b) and to all other roles (Panels c and d). The main independent variable is $InflowsAtTies$, recalculated so that ties are active between 2 and 12 quarters after a coworker transition (Panels a and c) and 4 and 20 quarters (Panels b and d), respectively. The coefficients come from separate models on a series of leads and lags of inflows at ties. The inflows at ties measure is standardized to a mean of zero and a standard deviation of one. The figure shows 95 percent confidence intervals calculated using two-way clustered standard errors at the lender and year-quarter level.

Figure A5: Unique Number of Connected Banks Over Time




*Notes*: The figure plots, over time, the number of distinct banks with non-zero hiring and at least one active tie to a bank in our main estimation sample.

# B Additional Tables

Table A1: Summary Statistics: Dealscan Loan-Level Data

| | N | Mean | SD | P25 | P50 | P75 |
|---|---|---|---|---|---|---|
| Borrower Prime | 55,327 | 0.30 | 0.46 | 0.00 | 0.00 | 1.00 |
| Borrower Rating | 55,327 | 0.46 | 0.20 | 0.25 | 0.50 | 0.62 |
| Tranche Amount | 55,327 | 905.00 | 1,623.00 | 150.00 | 400.00 | 1,000.00 |
| Maturity | 55,327 | 50.00 | 23.00 | 36.00 | 58.00 | 60.00 |
| Secured | 55,327 | 0.51 | 0.50 | 0.00 | 1.00 | 1.00 |
| Covenants | 55,327 | 0.48 | 0.50 | 0.00 | 0.00 | 1.00 |

*Notes*: The table reports loan-tranche level summary statistics for our sample of Dealscan loans. Included are loan observations by the largest 1500 lead arranging banks. *Borrower Prime* is an indicator for investment-grade borrowers. *Borrower Rating* is an ordinal borrower rating normalized to range between 0 and 1. *Tranche Amount* is converted to million USD. *Maturity* is indicated in months. *Secured* is an indicator for whether or not the tranche is secured. *Covenants* is an indicator for whether or not financial covenants exist.

Table A2: Summary Statistics: Employment History Data

| | | | Weighted | | | | |
|---|---|---|---|---|---|---|---|
| | N | Mean | Mean | SD | P25 | P50 | P75 |
| **Panel A: Full Sample** | | | | | | | |
| Male | 801,049 | 0.69 | 0.68 | 0.46 | 0.00 | 1.00 | 1.00 |
| White | 802,908 | 0.78 | 0.78 | 0.42 | 1.00 | 1.00 | 1.00 |
| Bachelor | 634,528 | 0.50 | 0.50 | 0.50 | 0.00 | 1.00 | 1.00 |
| More than Bachelor | 634,528 | 0.48 | 0.48 | 0.50 | 0.00 | 0.00 | 1.00 |
| Salary (in 1000) | 803,076 | 150.06 | 149.55 | 69.22 | 102.56 | 135.27 | 181.38 |
| Age at Start | 771,951 | 33.55 | 33.53 | 8.18 | 28.20 | 32.60 | 38.40 |
| Age at Middle | 771,951 | 36.69 | 36.66 | 8.28 | 30.85 | 35.68 | 41.71 |
| Age at End | 771,951 | 39.83 | 39.80 | 9.69 | 32.91 | 38.31 | 45.36 |
| Seniority | 803,096 | 4.75 | 4.75 | 0.74 | 4.00 | 5.00 | 5.00 |
| Nr. of Previous Positions | 803,096 | 3.02 | 3.03 | 2.62 | 1.00 | 3.00 | 4.00 |
| **Panel B: Matched Sample** | | | | | | | |
| Age | 327 | 40.28 | 40.27 | 7.93 | 35.10 | 40.00 | 45.34 |
| Seniority | 327 | 4.76 | 4.76 | 0.90 | 5.00 | 5.00 | 5.00 |
| Job Tenure | 327 | 9.04 | 9.05 | 7.31 | 3.48 | 7.20 | 12.47 |
| Salary (in $1000) | 327 | 224.62 | 224.49 | 89.16 | 169.11 | 200.57 | 269.28 |

*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 that are 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 1000 USD. The age variables refer to the beginning, middle, and end of an employment spell. *Seniority* refers to the seniority ranking, taking values between 4 (lowest) and 7 (highest). *Nr. of Previous Positions* counts the number of positions held prior to the current spell. The sample in Panel B shows demographic summary statistics on the sample of bankers matched to individual loans, focusing on the date of loan signature. *Age* and *Job Tenure* are precise values in years, *Seniority* refers to the seniority ranking, taking values between 0 (lowest) and 7 (highest). *Salary* is an imputed variable based on observable characteristics of an employment spell and measured in 1000 USD. The variable *Weighted Mean* exploits sampling weights constructed by Revelio Labs (see here for details).

Table A3: Summary Statistics: Employment History Data vs. Administrative 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 | 1,657.54 | 20.23 | 304.14 |

*Notes*: The table reports spell-level weighted averages of demographic variables, comparing the employment biography data against demographic sources. *Estimation Sample* includes all employment spells that are 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 of the employment spell data. *CPS* and *ACS* rely on administrative 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 of individuals that are in the labor force, at work and in full-time employment, below 66 years, and with hourly income of at least 10 USD (21600 USD annually). We restrict the sample to employment in the financial industry (1990 industry classification code between 700 and 710) and occupations related to loan origination (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 1000 USD. For the employment history data, it is an imputed measure based on observable characteristics of an employment spell. *Age* refers to age at the middle of employment spell for the spell-level data. *Observations* shows the number of observations that are non-missing for all of the above 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 Liabilities | 55,327 | 2,651.48 | 19,409.86 | 10.00 | 74.20 | 503.00 |
| Long Term Liabilities | 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 |
| **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 Liabilities | 55,327 | 176,537.77 | 130,782.04 | 73,136.00 | 161,592.54 | 262,878.00 |
| Long Term Liabilities | 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: (Conditional) Value at Risk** | | | | | | |
| Value At Risk ($95^{th}$ Pctile) | 10,635 | -0.08 | 23.00 | -12.00 | -0.85 | 11.00 |
| Conditional Value at Risk ($95^{th}$ Pctile) | 10,635 | -0.07 | 21.00 | -10.00 | -0.80 | 9.60 |
| Value At Risk ($99^{th}$ Pctile) | 10,635 | -0.05 | 21.00 | -11.00 | -0.63 | 10.00 |
| Conditional Value at Risk ($99^{th}$ Pctile) | 10,635 | -0.04 | 21.00 | -9.90 | -0.45 | 9.30 |
| **Panel D: Compensation Data** | | | | | | |
| Median Salary (in $1000) | 8,457 | 784.00 | 393.00 | 506.00 | 767.00 | 1,000.00 |
| Median Bonus (in $1000) | 8,457 | 579.00 | 1,745.00 | 0.00 | 0.00 | 600.00 |
| Median Equity at Risk (in $1000) | 8,333 | 9,170.00 | 19,784.00 | 2,342.00 | 5,672.00 | 11,147.00 |
| Median Salary (Growth, in Ppt.) | 8,462 | 3.60 | 27.00 | 0.00 | 2.70 | 9.90 |
| Median Bonus (Growth, in Ppt.) | 8,462 | -4.40 | 85.00 | 0.00 | 0.00 | 1.50 |
| Median Equity at Risk (Growth, in Ppt.) | 8,462 | 2.60 | 75.00 | -36.00 | 0.00 | 43.00 |

*Notes*: This table reports summary statistics for the borrower (Panel A) firm and lender firm (Panel B) control variables in the loan level sample. Variables are taken from the Compustat Fundamentals Annual North America and Global databases. Total assets, total liabilities, capital expenditures, earnings before interest and taxes (EBIT), net income, current liabilities, long-term liabilities and stockholders' equity are given in million USD. Employee counts are given in thousands. Panel C shows summary statistics of (Conditional) Value at Risk, obtained from Adrian and Brunnermeier (2016). The data are at quarterly frequency and span the period between 1994 and 2009. All variables are in symmetric growth rates and transformed into percentage points. Panel D shows summary statistics of compensation data from BoardEx, showing averages of salaries, bonuses, and equity at risk of senior non-executive bankers at the bank-year level. Growth is constructed in terms of symmetric rates. The data are drawn from BoardEx and span the period between 1997 and 2020.

Table A5: Summary Statistics: Outside Options Measure

| | N | Mean | SD | P25 | P50 | P75 |
|---|---|---|---|---|---|---|
| Nr. of Employees | 19,378 | 316.77 | 750.68 | 19.00 | 82.00 | 258.00 |
| Nr. of Connected Bankers | 19,378 | 40.34 | 105.46 | 2.00 | 8.00 | 29.00 |
| Nr. of Bank-Level Ties | 19,378 | 23.58 | 45.27 | 2.00 | 7.00 | 23.00 |
| Nr. of Bank-Level Ties (Size-corrected) | 19,378 | 13.12 | 15.68 | 2.00 | 6.40 | 18.28 |
| Nr. of Bank-Level Ties With Positive Inflows | 19,378 | 11.54 | 20.49 | 1.00 | 3.00 | 13.00 |
| Average Job-to-Job Hiring at Ties | 19,378 | 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 A6: Validation: Outside Options and Bank-Level Covariates in Levels

| | IAT Lead 1Q | IAT Lead 2Q | IAT Lead 3Q | IAT Lead 4Q |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Log Assets | -0.338 | -0.313 | -0.319 | -0.333 |
| | (0.343) | (0.328) | (0.334) | (0.343) |
| Log EBIT | 0.005 | 0.005 | 0.012 | 0.028 |
| | (0.040) | (0.035) | (0.034) | (0.034) |
| Log Current Liabilities | 0.113* | 0.072 | 0.052 | 0.049 |
| | (0.064) | (0.075) | (0.084) | (0.089) |
| Log Long-Term Debt | -0.120 | -0.144 | -0.133 | -0.131 |
| | (0.174) | (0.179) | (0.174) | (0.173) |
| Log Liabilities | 0.473 | 0.450 | 0.432 | 0.422 |
| | (0.368) | (0.357) | (0.351) | (0.346) |
| Log Equity | 0.019 | 0.014 | 0.027 | 0.023 |
| | (0.081) | (0.079) | (0.079) | (0.076) |
| Log Capital Expenditures | -0.176 | -0.124 | -0.121 | -0.112 |
| | (0.115) | (0.128) | (0.133) | (0.142) |
| Log Net Income | -0.007 | 0.0007 | 0.001 | 0.003 |
| | (0.028) | (0.025) | (0.021) | (0.021) |
| Lender fixed effects | X | X | X | X |
| Year-Quarter fixed effects | X | X | X | X |
| Observations | 11,964 | 11,964 | 11,964 | 11,964 |

*Notes*: The table reports results from regressing future values (one to four quarters ahead) of inflows at ties on current bank-level covariates, conditional on fixed effects at the lender and year-quarter level. Standard errors clustered at the lender level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Validation: Outside Options and Bank-Level Covariates in Growth Rates

| | IAT Lead 1Q | IAT Lead 2Q | IAT Lead 3Q | IAT Lead 4Q |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Asset Growth | -0.217 | 0.206 | 0.201 | 0.180 |
| | (0.573) | (0.666) | (0.657) | (0.658) |
| EBIT Growth | -0.008 | 0.002 | 0.022 | 0.038** |
| | (0.022) | (0.019) | (0.018) | (0.017) |
| Current Liabilities Growth | 0.111* | 0.076* | 0.044 | 0.036 |
| | (0.059) | (0.041) | (0.034) | (0.038) |
| Long-Term Debt Growth | 0.008 | 0.006 | -0.011 | -0.018 |
| | (0.211) | (0.218) | (0.205) | (0.187) |
| Liabilities Growth | 0.170 | -0.017 | -0.047 | 0.024 |
| | (0.473) | (0.452) | (0.441) | (0.415) |
| Equity Growth | 0.009 | 0.004 | 0.018 | 0.021 |
| | (0.042) | (0.040) | (0.046) | (0.043) |
| Capital Expenditures Growth | -0.025 | 0.124 | 0.129 | 0.145 |
| | (0.158) | (0.101) | (0.113) | (0.145) |
| Net Income Growth | -0.016 | -0.009 | -0.008 | -0.004 |
| | (0.015) | (0.015) | (0.016) | (0.017) |
| Lender fixed effects | X | X | X | X |
| Year-Quarter fixed effects | X | X | X | X |
| Observations | 11,268 | 11,268 | 11,268 | 11,268 |

*Notes*: The table reports results from regressing future values (one to four quarters ahead) of inflows at ties on growth rates in current bank-level covariates, conditional on fixed effects at the lender and year-quarter level. Standard errors clustered at the lender level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Variation in Hiring at Connected Banks

| Fixed Effects | $R^2$ |
|---|---|
| $\text{Bank}_i$ | 0.025 |
| $\text{Bank}_i$ + Year-Quarter | 0.064 |
| $\text{Bank}_i \times$ Year-Quarter | 0.112 |
| $\text{Bank}_j$ | 0.598 |
| $\text{Bank}_j$ + Year-Quarter | 0.648 |
| $\text{Bank}_j$ + $\text{Bank}_i$ + Year-Quarter | 0.649 |
| $\text{Bank}_j$ + $\text{Bank}_i \times$ Year-Quarter | 0.675 |

*Notes*: The table reports $R^2$ obtained from regressing hiring at connected banks on varying combinations of fixed effects. $Bank_i$ refers to the bank of interest, $Bank_j$ to the connected bank.

Table A9: Effect of Outside Options on Lending Volumes (Ties Active from 2 to 12 Quarters)

| | Growth Rate | | Extensive Margin | | Log Volume | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | OLS | OLS | Logit | Logit | OLS | OLS |
| IAT | 1.69 | 1.68 | 0.262** | 0.281** | 0.019 | 0.015 |
| | (1.11) | (1.13) | (0.126) | (0.126) | (0.029) | (0.028) |
| Lender fixed effects | X | X | X | X | X | X |
| Year-Quarter fixed effects | X | X | X | X | X | X |
| Lender Controls | | X | | X | | X |
| Observations | 6,277 | 6,277 | 3,999 | 3,999 | 4,058 | 4,058 |

*Notes*: The table reports results from regressing the outcome of interest on $InflowsAtTies_{it}$, lender controls, and fixed effects at the lender and year-quarter level. The measure $InflowsAtTies$ is recalculated so that ties are active between 2 and 12 quarters after a coworker transition, rather than between 4 and 12 quarters as in the baseline. The outcome variables are symmetric growth rates of total lending volume in percentage points (Columns 1 and 2), an indicator equal to one if a bank arranged any loan (Columns 3 and 4), and the natural logarithm of the loan amount, conditional on lending a strictly positive amount (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. Columns (1), (2), (5), and (6) are estimated via OLS, while Columns (3) and (4) are obtained from logit regressions. Standard errors are double-clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Effect of Outside Options on Lending Volumes (Ties Active from 4 to 20 Quarters)

| | Growth Rate | | Extensive Margin | | Log Volume | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | OLS | OLS | Logit | Logit | OLS | OLS |
| IAT | 2.25*** | 2.21** | 0.181* | 0.192* | 0.014 | 0.005 |
| | (0.843) | (0.893) | (0.103) | (0.104) | (0.032) | (0.031) |
| Lender fixed effects | X | X | X | X | X | X |
| Year-Quarter fixed effects | X | X | X | X | X | X |
| Lender Controls | | X | | X | | X |
| Observations | 6,277 | 6,277 | 3,999 | 3,999 | 4,058 | 4,058 |

*Notes*: The table reports results from regressing the outcome of interest on $InflowsAtTies_{it}$, lender controls, and fixed effects at the lender and year-quarter level. The measure $InflowsAtTies$ is recalculated so that ties are active between 4 and 20 quarters after a coworker transition, rather than between 4 and 12 quarters as in the baseline. The outcome variables are symmetric growth rates of total lending volume in percentage points (Columns 1 and 2), an indicator equal to one if a bank arranged any loan (Columns 3 and 4), and the natural logarithm of the loan amount, conditional on lending a strictly positive amount (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. Columns (1), (2), (5), and (6) are estimated via OLS, while Columns (3) and (4) are obtained from logit regressions. Standard errors are double-clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: Effect of Outside Options on Changes in Financial Risk (in Percentage Points, Ties Active from 2 to 12 Quarters)

| | VaR 95% | | CoVaR 95% | | VaR 99% | | CoVaR 99% | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| IAT | 0.254 | 0.255 | 0.204 | 0.202 | 0.425*** | 0.421*** | 0.385*** | 0.379*** |
| | (0.218) | (0.217) | (0.180) | (0.179) | (0.157) | (0.155) | (0.136) | (0.133) |
| Lender fixed effects | X | X | X | X | X | X | X | X |
| Year-Quarter fixed effects | X | X | X | X | X | X | X | X |
| Lender Controls | | X | | X | | X | | X |
| Observations | 10,635 | 10,635 | 10,635 | 10,635 | 10,635 | 10,635 | 10,635 | 10,635 |

*Notes*: The table reports coefficients from OLS regressions of symmetric growth rates in VaR and CoVaR (in percentage points) on $InflowsAtTies_{it}$, lender controls, and fixed effects at the lender and year-quarter level. The measure $InflowsAtTies$ is recalculated so that ties are active between 2 and 12 quarters after a coworker transition, rather than between 4 and 12 quarters as in the baseline. The outcomes are VaR (Columns 1, 2, 5 and 6) and CoVaR (Columns 3, 4, 7 and 8), computed at the 95% confidence level (Columns 1 to 4) and the 99% confidence level (Columns 5 to 8). 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 double-clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A12: Effect of Outside Options on Changes in Financial Risk (in Percentage Points, Ties Active from 4 to 20 Quarters)

| | VaR 95% | | CoVaR 95% | | VaR 99% | | CoVaR 99% | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| IAT | 0.406* | 0.408* | 0.336* | 0.333* | 0.411** | 0.407** | 0.355* | 0.348** |
| | (0.217) | (0.214) | (0.174) | (0.171) | (0.201) | (0.199) | (0.179) | (0.175) |
| Lender fixed effects | X | X | X | X | X | X | X | X |
| Year-Quarter fixed effects | X | X | X | X | X | X | X | X |
| Lender Controls | | X | | X | | X | | X |
| Observations | 10,749 | 10,749 | 10,749 | 10,749 | 10,749 | 10,749 | 10,749 | 10,749 |

*Notes*: The table reports coefficients from OLS regressions of symmetric growth rates in VaR and CoVaR (in percentage points) on $InflowsAtTies_{it}$, lender controls, and fixed effects at the lender and year-quarter level. The measure $InflowsAtTies$ is recalculated so that ties are active between 4 and 20 quarters after a coworker transition, rather than between 4 and 12 quarters as in the baseline. The outcomes are VaR (Columns 1, 2, 5 and 6) and CoVaR (Columns 3, 4, 7 and 8), computed at the 95% confidence level (Columns 1 to 4) and the 99% confidence level (Columns 5 to 8). 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 double-clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A13: Borrower Characteristics and Investment-Grade Status

| | Borrower Prime | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Borrower Assets (log) | 0.056*** | | | | | | | | |
| | (0.006) | | | | | | | | |
| Borrower Capex (log) | | 0.015*** | | | | | | | |
| | | (0.004) | | | | | | | |
| Borrower Employees (log) | | | 0.041*** | | | | | | |
| | | | (0.006) | | | | | | |
| Borrower Liabilities (log) | | | | 0.049*** | | | | | |
| | | | | (0.005) | | | | | |
| Borrower EBIT (log) | | | | | 0.030*** | | | | |
| | | | | | (0.002) | | | | |
| Borrower Net Income (log) | | | | | | 0.026*** | | | |
| | | | | | | (0.002) | | | |
| Borrower Current Debt (log) | | | | | | | 0.022*** | | |
| | | | | | | | (0.003) | | |
| Borrower Total Debt (log) | | | | | | | | 0.026*** | |
| | | | | | | | | (0.004) | |
| Borrower Equity (log) | | | | | | | | | 0.009*** |
| | | | | | | | | | (0.002) |
| Lender fixed effects | X | X | X | X | X | X | X | X | X |
| Year-Quarter fixed effects | X | X | X | X | X | X | X | X | X |

*Notes*: The table reports results from regressing an indicator for investment-grade borrower status on borrower characteristics, one per Column, each entered as its inverse hyperbolic sine transformation. All Columns include fixed effects at the lender and year-quarter level. Standard errors, double-clustered at the lender and year-quarter level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A14: Effect of Outside Options on Lender Risk—Robustness

| Sample | Borrower Prime | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Full Sample | | | | | | | Post 2008 | Origination |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| IAT | -0.006*** | -0.007** | -0.010*** | -0.006*** | -0.005*** | -0.005*** | -0.005*** | -0.004*** | -0.008*** |
| | (0.002) | (0.003) | (0.003) | (0.001) | (0.001) | (0.001) | (0.002) | (0.0008) | (0.001) |
| Outflows | | | | | 0.011 | | | | |
| | | | | | (0.007) | | | | |
| Number of Lenders | | | | | | -0.0002 | | | |
| | | | | | | (0.008) | | | |
| IAC | | | | | | | -0.005 | | |
| | | | | | | | (0.003) | | |
| Lender fixed effects | X | X | X | | X | X | X | X | X |
| Year-Quarter fixed effects | X | X | X | X | X | X | X | X | X |
| Borrower SIC Sector × Year-Quarter fixed effects | | X | | | | | | | |
| Borrower State × Year-Quarter fixed effects | | | X | | | | | | |
| Lender × Year fixed effects | | | | X | | | | | |
| IAT Leads and Lags | X | | | | | | | | |
| Borrower Controls | X | X | X | X | X | X | X | X | X |
| Lender Controls | X | X | X | | X | X | X | X | X |
| Loan Controls | X | X | X | X | X | X | X | X | X |
| Observations | 55,327 | 52,475 | 50,131 | 55,278 | 55,327 | 55,327 | 49,959 | 44,523 | 25,400 |

*Notes*: The table reports results from robustness exercises for Column (3) of Table 4, obtained by estimating Equation (12) at the loan level. The dependent variable in all regressions is an indicator for investment-grade borrowers. The independent variable is $InflowsAtTies_{it}$. Borrower and lender controls include the inverse hyperbolic sine transformation of total assets, number of employees, capital expenditure, total liabilities, EBIT, and (for borrowers) fixed assets. Loan controls are the inverse hyperbolic sine transformation of tranche amount and maturity, and indicators for whether the loan is secured, and whether covenants are attached. All regressions include fixed effects at the lender and year-quarter level. Standard errors are double-clustered at the lender and year-quarter level. Compared to Column (3) of Table 4, the following additional variables are included: (1) 4 lags and leads of $InflowsAtTies_{it}$; (2) borrower-SIC × year-quarter fixed effects; (3) borrower-state × year-quarter fixed effects; (4) lender × year fixed effects; (5) the inverse hyperbolic sine transformation of outflows; (6) the inverse hyperbolic sine transformation of the number of lenders; (7) IAC ($InflowsAtCosignatories_{it}$), a variant of $InflowsAtTies_{it}$ where we replace the ties from coworker networks by the ties resulting from co-arranging loans. In Column (8), we restrict the sample to loans in 2008 and afterwards. In Column (9), we restrict the sample to new originations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A15: Effect of Outside Options on Borrower Risk (Ties Active from 2 to 12 Quarters)

| | Borrower Prime | | | Borrower Rating | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| IAT | -0.002 | -0.005*** | -0.005*** | 0.0002 | -0.002** | -0.002** |
| | (0.001) | (0.001) | (0.001) | (0.0010) | (0.0006) | (0.0006) |
| Lender fixed effects | X | X | X | X | X | X |
| Year-Quarter fixed effects | X | X | X | X | X | X |
| Lender Controls | X | X | X | X | X | X |
| Borrower Controls | | X | X | | X | X |
| Loan Controls | | | X | | | X |
| Outcome Mean | 0.296 | 0.296 | 0.296 | 0.462 | 0.462 | 0.462 |
| Observations | 55,327 | 55,327 | 55,327 | 55,327 | 55,327 | 55,327 |

*Notes*: The table reports results from estimating Equation (12) at the loan level. The dependent variables are an indicator for investment-grade borrowers (Columns 1 to 3) and an ordinal borrower rating normalized to range between 0 and 1 (Columns 4 to 6). The measure $InflowsAtTies$ is recalculated so that ties are active between 2 and 12 quarters after a coworker transition, rather than between 4 and 12 quarters as in the baseline. The independent variable is $InflowsAtTies_{it}$. Borrower and lender controls include the inverse hyperbolic sine transformation of total assets, number of employees, capital expenditure, total liabilities, EBIT, and (for borrowers) fixed assets. Loan controls are the inverse hyperbolic sine transformation of tranche amount and maturity and indicators for whether the loan is secured and whether covenants are attached. All regressions include fixed effects at the lender and year-quarter level, and standard errors are double-clustered at the same levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A16: Effect of Outside Options on Borrower Risk (Ties Active from 4 to 20 Quarters)

| | Borrower Prime | | | Borrower Rating | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| IAT | -0.004*** | -0.006*** | -0.006*** | -0.0010 | -0.002*** | -0.002*** |
| | (0.001) | (0.001) | (0.001) | (0.0009) | (0.0006) | (0.0006) |
| Lender fixed effects | X | X | X | X | X | X |
| Year-Quarter fixed effects | X | X | X | X | X | X |
| Lender Controls | X | X | X | X | X | X |
| Borrower Controls | | X | X | | X | X |
| Loan Controls | | | X | | | X |
| Outcome Mean | 0.296 | 0.296 | 0.296 | 0.462 | 0.462 | 0.462 |
| Observations | 55,327 | 55,327 | 55,327 | 55,327 | 55,327 | 55,327 |

*Notes*: The table reports results from estimating Equation (12) at the loan level. The dependent variables are an indicator for investment-grade borrowers (Columns 1 to 3) and an ordinal borrower rating normalized to range between 0 and 1 (Columns 4 to 6). The measure $InflowsAtTies$ is recalculated so that ties are active between 4 and 20 quarters after a coworker transition, rather than between 4 and 12 quarters as in the baseline. The independent variable is $InflowsAtTies_{it}$. Borrower and lender controls include the inverse hyperbolic sine transformation of total assets, number of employees, capital expenditure, total liabilities, EBIT, and (for borrowers) fixed assets. Loan controls are the inverse hyperbolic sine transformation of tranche amount and maturity and indicators for whether the loan is secured and whether covenants are attached. All regressions include fixed effects at the lender and year-quarter level, and standard errors are double-clustered at the same levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A17: Effect of Outside Options on Loan Price

| | All-In-Spread-Drawn (log bps) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| IAT | -0.004 | 0.000 | 0.002 | -0.005 | -0.002 | 0.000 |
| | (0.006) | (0.005) | (0.003) | (0.005) | (0.005) | (0.003) |
| Lender fixed effects | X | X | X | X | X | X |
| Year-Quarter fixed effects | X | X | X | X | X | X |
| Borrower Rating fixed effects | | | | X | X | X |
| Lender Controls | X | X | X | X | X | X |
| Borrower Controls | | X | X | | X | X |
| Loan Controls | | | X | | | X |
| Outcome Mean | 5.935 | 5.935 | 5.935 | 5.935 | 5.935 | 5.935 |
| Observations | 47,760 | 47,760 | 47,760 | 47,760 | 47,760 | 47,760 |

*Notes*: The table reports results from estimating Equation (12) at the loan level. The dependent variable is the log all-in-spread-drawn (in basis points). The independent variable is $InflowsAtTies_{it}$. Borrower and lender controls include the inverse hyperbolic sine transformation of total assets, number of employees, capital expenditure, total liabilities, EBIT, and (for borrowers) fixed assets. Loan controls are the inverse hyperbolic sine transformation of tranche amount and maturity and indicators for whether the loan is secured and whether covenants are attached. All regressions include fixed effects at the lender and year-quarter level, and standard errors are double-clustered at the same levels. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table A18: Effect of Outside Options on Lender Risk by NCA Enforceability

| | Borrower Prime | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| IAT | -0.007** | -0.004 | -0.004 |
| | (0.003) | (0.004) | (0.005) |
| IAT × Enforcement Change | 0.011 | | |
| | (0.011) | | |
| IAT × Enforcement Increase | | -0.013 | |
| | | (0.011) | |
| IAT × Enforcement Decrease | | | -0.036*** |
| | | | (0.011) |
| Lender fixed effects | X | X | X |
| Year-Quarter fixed effects | X | X | X |
| State-Year fixed effects | X | X | X |
| Lender Controls | X | X | X |
| Borrower Controls | X | X | X |
| Loan Controls | X | X | X |
| Outcome Mean | 0.296 | 0.296 | 0.296 |
| Observations | 50,490 | 50,490 | 50,490 |

*Notes*: The table reports a robustness exercise for Column (3) of Table 4, estimating Equation (12) at the loan level. The dependent variable in all Columns is an indicator for investment-grade borrowers. The main independent variable is $InflowsAtTies_{it}$, interacted with measures of changes in Non-Compete Agreement (NCA) enforceability in the state of the bank's headquarters. *Enforcement Change* equals 1 if a state increased its NCA enforceability and −1 if it decreased it, in any past or current period, and 0 otherwise; *Enforcement Increase* and *Enforcement Decrease* are separate indicators for past increases and decreases. Borrower and lender controls include the inverse hyperbolic sine transformation of total assets, number of employees, capital expenditure, total liabilities, EBIT, and (for borrowers) fixed assets. Loan controls are the inverse hyperbolic sine transformation of tranche amount and maturity and indicators for whether the loan is secured and whether covenants are attached. All Columns include fixed effects at the lender and year-quarter level and at the state-year level. Standard errors are double-clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A19: Effect of Outside Options on Borrower Rating: Age Heterogeneity

| | Borrower Prime Rating (Normalized) | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| IAT | -0.321** | -0.335** | -0.331** | | | | |
| | (0.124) | (0.143) | (0.152) | | | | |
| IAT × Age | 0.008** | 0.008** | 0.008** | 0.005*** | 0.005*** | 0.005*** | 0.004* |
| | (0.003) | (0.003) | (0.003) | (0.001) | (0.001) | (0.001) | (0.002) |
| Lender fixed effects | X | X | X | | | | |
| Year-Quarter fixed effects | X | X | X | | | | |
| Banker fixed effects | X | X | X | X | X | X | X |
| Lender × Year-Quarter fixed effects | | | | X | X | | X |
| MSA × Year-Quarter fixed effects | | | | | X | | X |
| Lender × MSA × Year-Quarter fixed effects | | | | | | X | |
| Lender Controls | X | X | X | | | | |
| Borrower Controls | | X | X | X | X | X | X |
| Loan Controls | | | X | X | X | X | X |
| IAT × Spell Controls | | | | | | | X |
| Outcome Mean | 0.495 | 0.495 | 0.434 | 0.488 | 0.488 | 0.488 | 0.500 |
| Observations | 275 | 275 | 275 | 327 | 327 | 327 | 327 |

*Notes*: The table reports results from estimating Equation (12) at the loan level, augmented with an interaction for the underwriting banker's age. The dependent variable is an ordinal scale of borrower rating, normalized to range between 0 and 1. The independent variables are $InflowsAtTies_{it}$ and its interaction with the banker's age. Borrower and lender controls include the inverse hyperbolic sine transformation of total assets, number of employees, capital expenditure, total liabilities, EBIT, and (for borrowers) fixed assets. Loan controls are the inverse hyperbolic sine transformation of tranche amount and maturity, and indicators for whether the loan is secured, and whether covenants are attached. *Spell controls* contains the position number, the seniority level, the inverse hyperbolic sine transformation of imputed salary and job tenure, each included interacted with $InflowsAtTies_{it}$ and (if possible) as a standalone variable. Standard errors are double-clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A20: Effect of Outside Options on Tranche Amounts: Age Heterogeneity

| | Asinh (Tranche Amount) | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| IAT | -1.34 | 0.322 | 0.358 | | | | |
| | (0.770) | (0.569) | (0.449) | | | | |
| IAT × Age | 0.035*** | 0.008 | 0.008 | -0.031*** | -0.030** | -0.030** | -0.044*** |
| | (0.009) | (0.008) | (0.008) | (0.010) | (0.010) | (0.010) | (0.009) |
| Lender fixed effects | X | X | X | | | | |
| Year-Quarter fixed effects | X | X | X | | | | |
| Banker fixed effects | X | X | X | X | X | X | X |
| Lender × Year-Quarter fixed effects | | | | X | X | | X |
| MSA × Year-Quarter fixed effects | | | | | X | | X |
| Lender × MSA × Year-Quarter fixed effects | | | | | | X | |
| Lender Controls | X | X | X | | | | |
| Borrower Controls | | X | X | X | X | X | X |
| Loan Controls | | | X | X | X | X | X |
| IAT × Spell Controls | | | | | | | X |
| Outcome Mean | 6.90 | 6.90 | 6.89 | 6.80 | 6.80 | 6.79 | 6.62 |
| Observations | 322 | 322 | 322 | 383 | 383 | 383 | 383 |

*Notes*: The table reports results from estimating Equation (12) at the loan level, augmented with an interaction for the underwriting banker's age. The dependent variable is the inverse hyperbolic sine transformation of the tranche amount. The independent variables are $InflowsAtTies_{it}$ and its interaction with the banker's age. Borrower and lender controls include the inverse hyperbolic sine transformation of total assets, number of employees, capital expenditure, total liabilities, EBIT, and (for borrowers) fixed assets. Loan controls are the inverse hyperbolic sine transformation of maturity, and indicators for whether the loan is secured, and whether covenants are attached. *Spell controls* contains the position number, the seniority level, the inverse hyperbolic sine transformation of imputed salary and job tenure, each included interacted with $InflowsAtTies_{it}$ and (if possible) as a standalone variable. Standard errors are double-clustered at the lender and year-quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A21: Effect of Outside Options on Misconduct Disclosures

| | Number of Misconduct Disclosures | | | | | | Binarized |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| $IAT_{t-1}$ | 0.003*** | 0.003*** | 0.003*** | 0.003*** | 0.002*** | 0.004*** | 0.003*** |
| | (0.0009) | (0.0009) | (0.0008) | (0.0008) | (0.0006) | (0.0009) | (0.0008) |
| $IAT_t$ | | | | | 0.003** | | |
| | | | | | (0.001) | | |
| $IAT_{t-2}$ | | | | | -0.0008 | | |
| | | | | | (0.0005) | | |
| $Outflows_{t-1}$ | | | | | | 0.003 | |
| | | | | | | (0.002) | |
| Lender fixed effects | X | X | | | | | |
| Year fixed effects | X | X | X | | X | X | X |
| Advisor fixed effects | | X | | | | | |
| Lender × Advisor fixed effects | | | X | X | X | X | X |
| State × Year fixed effects | | | | X | | | |
| Lender Controls | X | X | X | X | X | X | X |
| Outcome Mean | 0.010 | 0.010 | 0.009 | 0.009 | 0.009 | 0.009 | 0.009 |
| Observations | 582,568 | 561,018 | 551,079 | 551,079 | 551,079 | 551,079 | 551,079 |

*Notes*: The table reports results from estimating Equation (12) at annual frequency at the advisor level. The dependent variable is the number of misconduct disclosures an advisor had in a given year, which is binarized in Column (7). 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 the contemporaneous and the second lag of inflows at ties. Column (6) controls for the inverse hyperbolic sine transformation of lagged outflows. All models are estimated with year fixed effects and lender controls. Standard errors are clustered at the lender level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A22: Effect of Outside Options on Customer Complaints

| | Number of Customer Complaints | | | | | | Binarized |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| $IAT_{t-1}$ | 0.005*** | 0.006*** | 0.006*** | 0.005*** | 0.003*** | 0.006*** | 0.004*** |
| | (0.002) | (0.002) | (0.001) | (0.002) | (0.001) | (0.001) | (0.001) |
| $IAT_t$ | | | | | 0.005* | | |
| | | | | | (0.003) | | |
| $IAT_{t-2}$ | | | | | 0.0002 | | |
| | | | | | (0.001) | | |
| $Outflows_{t-1}$ | | | | | | 0.003 | |
| | | | | | | (0.004) | |
| Lender fixed effects | X | X | | | | | |
| Year fixed effects | X | X | X | | X | X | X |
| Advisor fixed effects | | X | | | | | |
| Lender × Advisor fixed effects | | | X | X | X | X | X |
| State × Year fixed effects | | | | X | | | |
| Lender Controls | X | X | X | X | X | X | X |
| Outcome Mean | 0.018 | 0.017 | 0.017 | 0.017 | 0.017 | 0.017 | 0.017 |
| Observations | 582,568 | 561,018 | 551,079 | 551,079 | 551,079 | 551,079 | 551,079 |

*Notes*: The table reports results from estimating Equation (12) at annual frequency at the advisor level. The dependent variable is the number of complaints filed against the advisor in a given year, which is binarized in Column (7). 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 the contemporaneous and the second lag of inflows at ties. Column (6) controls for the inverse hyperbolic sine transformation of lagged outflows. All models are estimated with year fixed effects and lender controls. Standard errors are clustered at the lender level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A23: Effect of Outside Options on Settled Customer Complaints

| | Number of Settled Customer Complaints | | | | | | Binarized |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| $IAT_{t-1}$ | 0.004*** | 0.004*** | 0.004*** | 0.004*** | 0.003*** | 0.004*** | 0.003*** |
| | (0.001) | (0.001) | (0.0010) | (0.0009) | (0.0007) | (0.001) | (0.0007) |
| $IAT_t$ | | | | | 0.004* | | |
| | | | | | (0.002) | | |
| $IAT_{t-2}$ | | | | | -0.0005 | | |
| | | | | | (0.0008) | | |
| $Outflows_{t-1}$ | | | | | | 0.003 | |
| | | | | | | (0.003) | |
| Lender fixed effects | X | X | | | | | |
| Year fixed effects | X | X | X | | X | X | X |
| Advisor fixed effects | | X | | | | | |
| Lender × Advisor fixed effects | | | X | X | X | X | X |
| State × Year fixed effects | | | | X | | | |
| Lender Controls | X | X | X | X | X | X | X |
| Outcome Mean | 0.008 | 0.008 | 0.008 | 0.008 | 0.008 | 0.008 | 0.008 |
| Observations | 582,568 | 561,018 | 551,079 | 551,079 | 551,079 | 551,079 | 551,079 |

*Notes*: The table reports results from estimating Equation (12) at annual frequency at the advisor level. The dependent variable is the number of settled customer complaints an advisor had in a given year, which is binarized in Column (7). 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 the contemporaneous and the second lag of inflows at ties. Column (6) controls for the inverse hyperbolic sine transformation of lagged outflows. All models are estimated with year fixed effects and lender controls. Standard errors are clustered at the lender level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.