Credit and Punishment:
The Career Incentives of Wall Street Bankers

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Abstract

This study examines the relationship between negative credit events (i.e., defaults, bankruptcies, and rating downgrades), loan contracting, and career turnover for Wall Street bankers underwriting syndicated loans. We construct a comprehensive dataset containing the identities and employment histories of nearly 1,500 bankers employed by major corporate banking departments from the period spanning 1994 to 2014. Following a negative credit shock in a banker's portfolio, the banker is more likely to depart her bank, transition to a lower-ranked bank, and face a demotion in the future. On the other hand, bankers who issue elevated levels of loans are more likely to receive internal promotions, suggesting that conflicting incentives exist in a bank. In addition, we confirm that the threat of termination can effectively incentivize bankers to impose stricter lending terms on future loans (i.e., more covenants and stricter covenants). Overall, our findings confirm that Wall Street bankers are disciplined for large-scale credit losses.

Key words: Syndicated Loans, Credit Events, Career Outcomes, Corporate Bankers, Bank Risk Management

JEL classification: G20, G21, G30, J24, J63

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1 Introduction

In the aftermath of the Global Financial Crisis, regulators have expressed renewed concerns regarding misaligned incentives prevalent in the banking industry. Financial sector losses impose significant externalities on economic growth (Khwaja and Mian (2005), Paravisini (2008)) and regulators have thus sought to better understand what incentives are in place to encourage healthy risk management. One important question that has arisen is whether employees in the financial services sector are held accountable and disciplined for excessive risk-taking. And, if so, do such disciplining mechanisms provide a sufficient disincentive in limiting future risk-taking behavior?

In this study, we shed light on these issues by examining whether Wall Street bankers working in corporate banking departments are disciplined for large-scale credit losses. In particular, we examine whether banks terminate bankers responsible for initiating and monitoring poorly performing loans, and whether such termination practices have long-term implications for a banker's career trajectory and future contracting tendencies. We construct a novel sample containing the identities and employment histories of 1,436 corporate bankers observed in over 2,500 SEC credit agreements over the period spanning from 1994 to 2014. We focus on the corporate banking market given its important role in firm financing (Roberts (2015)). Importantly, recent evidence also indicates that corporate bankers have significant influence on loan terms and loan performance (Gao et al. (2017), Herpfer (2017)), indicating that the individuals we identify in SEC credit agreements are likely to be responsible for structuring credit agreements.

Ex ante, there are strong reasons to expect that Wall Street bankers are disciplined for large-scale credit losses. First, credit losses are costly to shareholders (Demirguc-Kunt et al. (2013)) and negatively impact a bank's reputation, thus damaging syndicate relationships (Gopalan et al. (2012)). Thus, syndicated lenders have incentives to discipline bankers against risk-taking. Second, banks depend on loan performance to learn about underlying risk exposure. Prior studies find that banks decrease the credit supply (Chava and Purnanandam (2011)) and increase risk management (Murfin (2012)) following a credit event. Therefore, it is natural to assume that banks might use negative credit events as a signal to learn about the performance of individual bankers and terminate poor performers.

Yet, in contrast to these arguments, recent evidence suggests that the public has little trust in the incentive structure of Wall Street bankers and strongly believes in the need for greater regulation (Sapienza and Zingales (2013)). Recent academic studies corroborate this view. For example, bankers underwriting mortgage-backed securities appear to face no career consequences following the 2008 Financial Crisis (Griffin et al. (2016)), potentially due to practices that promote short-term gains at the expense of long-term performance (Bolton et al. (2006)) . Similarly, brokerage firms frequently hire financial advisors with a history of infractions suggesting that the market does not discipline these advisors' prior misconduct (Egan et al. (2016)). Prior studies also struggle to establish that executive incentives reduce risk-taking in the banking sector (Fahlenbrach and Stulz (2011)). Overall, prior studies offer limited direct evidence of effective incentive mechanisms in place in the financial sector. Understanding whether banks internally promote high quality lending standards through the threat of termination remains an empirical question.

We begin our analysis by confirming that the bankers in our sample are indeed directly responsible for structuring the credit agreements we observe. Accordingly, we conduct two sets of analyses that help to confirm this assumption. First, we show that the past experiences of a loan officer influences her current terms, even after controlling for other loan characteristics. In comparison, the past experiences of the other bankers in the firm have no influence on current terms. Second, we also replicate the fixed effects analyses conducted in Gao et al. (2017) and Herpfer (2017) and find that loan officers explain up to three to eight times more variation in loan performance in our sample than do the banks that employ then. Overall, this preliminary evidence suggests that bankers do indeed have an important economic effect on loan performance and that it is reasonable to attribute poor loan performance to these bankers.[1]

Having confirmed that the bankers in our sample have significant influence in corporate banking activities, we next summarize the dynamics of banker turnover. We first describe patterns in banker turnover. Over the course of the sample period, we observe 720 banker departures. This statistic implies that the likelihood of bankers departing from their current place of employment is around 5%. Moreover, we find that this figure has remained relatively steady over time and is also consistent across the top ten banks dominating the private loan market. These trends suggest that banker movement is generally not a very common event, and that

[1]Results are displayed in Appendix B.

termination can be a severe form of punishment for bankers. These trends are also consistent with anecdotal evidence indicating that the corporate banking market generally exhibits less turnover than other areas in finance.[2]

Our empirical objective is to examine whether patterns in banker turnover following negative credit events are consistent with banks incentivizing bankers to issue high quality loans. To this end, we examine regressions that estimate the likelihood of a banker departing her current place of employment in the period following a negative credit event. We consider negative credit events in which a borrower in a banker's portfolio experiences a rating downgrade, eventually defaults, or files for bankruptcy. Prior studies indicate that these event are economically important and impact banks' reputation, lending terms, and credit provisioning (Gopalan et al. (2011), Bushman and Wittenberg-Moerman (2012), Chava and Purnanandam (2011), Murfin (2012)).

The main findings indicate substantially higher levels of banker turnover following negative credit events in a banker's portfolio. Specifically, we find that negative credit events increase the relative likelihood the banker departs the bank by nearly 50%. Further, we find that the effect of negative credit events on banker turnover is pronounced when the credit event is severe (i.e., defaults and bankruptcies rather than downgrades) and when the banker is strongly affiliated with the loan (lead arranger versus participant). These results hold after controlling for differences across time, banks, borrowers and bankers, as well as characteristics of the loans and loan officer experience. Overall, the baseline analyses lend support to the argument that banks terminate bankers that issue risky loans.

In robustness analyses, we further examine whether and to what extent certain features of our sample explain our findings. We first examine whether our findings are influenced by the voluntary disclosure of debt contracts in SEC filings. We verify that our results persist among firms with high loan to asset ratios, an indicator that the loan agreement is likely to be material and filed with the SEC. We also examine whether our findings are driven by economic downturns or low quality information environments. We partition our sample based on recessionary periods and firm size, and find that our results hold outside of recession periods and among large firms, which are likely to be more transparent. We also consider that our sampling procedure may under-identify the deals that a loan officer is associated with as it relies on observing credit

[2]See for example `http://www.mergersandinquisitions.com/corporate-banking/`.

agreements in a firm's SEC filings. To this end, we construct a backfilled sample that assigns bankers to all of the loans issued for a given industry at a bank for the years in which we observe the bankers in our sample, and confirm that our results hold within this sample. Overall, our robustness analyses indicate that our sampling procedures do not unduly influence our findings.

While the above findings suggest an association between poor loan performance in a banker's portfolio and her departure from the bank, they do not provide causal evidence that banks terminate the banker because of negative credit events. Indeed, endogeneity is a common concern for studies examining employee movement as it is possible that unobserved characteristics of an employee explain both the employee's behavior prior to turnover as well as the turnover itself. In our case, the endogeneity concern is that unobserved time-varying characteristics of the banker explain both a banker's career trajectory as well as her lending standards.[3] To alleviate these concerns, we introduce a matched sample analysis to better control for time-varying changes in banker risk preferences that may affect the relationship between banker turnover and loan performance. For the bankers experiencing negative credit events (treated), we identify a matched (control) sample of bankers who did not experience negative credit events, but have recently participated in at least one overlapping loan syndicate, as these bankers are likely to exhibit similar risk preferences. We then compare the likelihood of departure for treated and control bankers, and find that treated bankers are more likely to depart their place of employment than are the matched control bankers. These findings suggest that time-varying risk preferences are unlikely to explain the positive association between negative credit events and banker turnover.

We next conduct additional analyses to better explore how career concerns impact bankers' behavior. First, we examine the career trajectories of bankers following negative credit events, and find that bankers that depart following negative credit events are more likely to face demotions and less likely to face promotions at their next employer. This result helps verify our claim that exit is not voluntary and also suggests that termination has powerful effects on an employee's reputation in the labor market (Fama 1980). Second, we examine whether positive incentives (e.g., bonuses) promote loan origination at the expense of credit quality. We find that bankers that extend elevated levels of loans are more likely to receive a promotion from their current employer, consistent with these bankers facing conflicting economic incentives to

[3]These endogeneity concerns, however, should only be related to time-varying unobserved heterogeneity in bankers since our analyses include banker-fixed effects.

issue risky loans at origination.

Having established a strong correlation between loan performance and banker career movements, we next examine how the performance-sensitivity relationship varies based on banker seniority. Recent evidence suggests that senior employees are less likely than junior employees to be punished for excessive risk-taking in the financial services industry (Griffin et al. (2016)). Accordingly, we split our sample based on loan officer title and tenure at the bank of interest. Our findings indicate that loan officers with more years of experience (i.e., greater than ten years) and higher ranked titles (i.e., Directors) are less likely to be terminated following negative credit events than are less experienced, lower-ranked bankers, suggesting that these bankers become entrenched in the firm over time.

To strengthen the claim that career turnovers serve as an incentive for bankers to impose stricter lending standards, we further explore how a banker's lending behavior modulates turnover risk following negative credit events. We find that bankers are more likely to depart following negative credit events when they issue lenient credit terms (i.e., fewer covenants and looser covenant thresholds). On the other hand, bankers who impose strict credit terms can often avoid turnover. These results suggest that strict lending terms alleviate the turnover-performance sensitivity of corporate bankers, indicating that the threat of termination might provide a sufficient disincentive against bankers issuing risky loans.

In our final set of tests, we turn to our second research question and investigate the effectiveness of career incentives in motivating higher quality lending standards. To do so, we test whether career concerns influence the future contract terms imposed by bankers, which ultimately affect firms' access to credit. In particular, we examine whether credit events influence the number of covenants and covenant strictness of new loans (Nikolaev (2010), Murfin (2012), Demerjian and Owens (2016)). In doing so, we focus on both the bankers responsible for issuing the poorly performing loans as well as their peers in the same bank. Examining the latter group helps shed light on how the observed termination practices serve as an ex ante disciplining mechanism across the bank.

In our first analysis of lending standards, we confirm that bankers issue loans with more covenants and higher levels of strictness following a negative credit event in their portfolio. This finding suggests that the threat of termination effectively motivates bankers to tighten their lending standards following negative credit events. We also find some evidence to suggest that bankers exhibit higher monitoring efforts following their peers' negative credit events, though the effect is smaller. One way of interpreting these findings is that the threat of termination encourages bankers to insure themselves by contracting on hard, verifiable accounting information as opposed to soft information.

In our second analysis of lending standards, we explore variation in the adoption of termination practices across the corporate lenders in our sample. To do so, we construct a bank-specific measure of termination-performance sensitivity (β) and examine whether and how a bank's termination practice relates to the lending terms issued by bankers in the bank. In a way, β gauges the risk culture within banks, and should serve to discipline lending behaviors. Our results suggest that bankers employed within banks that exhibit higher levels of termination threat have higher monitoring standards, as evidenced by their bankers issuing loans that require more covenants and have stricter covenant thresholds. Taken together, our lending terms analyses indicate that career incentives have a significant impact on loan terms. These effects extend beyond just a banker's own defaults and also impact her peers, suggesting that the implicit threat of termination can motivate better monitoring.

Overall, our paper contributes to the literature across several dimensions. First, we contribute to the call for more research examining how banks can influence and discipline employee behavior (Thakor (2015)). Our paper is most closely related to two concurrent studies. First, Griffin et al. (2016) examine the termination practices among mortgage backed securities originators and document very limited career incentives to discipline risk-taking amongst mortgage officers. In contrast, we examine risk-taking in the syndicated lending market, a market in which middle-tier employees can expose banks to substantial credit risks. Our findings suggest that banks frequently terminate corporate bankers following negative credit events and that career incentives can effectively influence bankers' lending standards. Second, Egan et al. (2016) find that fraudulent securities advisers often repeat misconduct despite the latent threat of termination. Our findings differ from Egan et al. (2016) in showing that termination practices can incentivize better risk management practices among corporate bankers.

Second, we contribute to studies examining bank risk-taking. Prior studies generally focus on risk-taking behavior among upper-level employees such as executives within a bank (e.g., Fahlenbrach et al. (2012), Ellul and Yerramilli (2013)). Recent studies emphasize the importance of mechanisms within the bank that also align the interests of lower-level employees (Acharya et al. (2013), Cole et al. (2015)). However, in practice, designing contracts to implement those mechanisms can be challenging due to information frictions inside banks, limited liabilities of bankers, and misaligned horizons between bankers and shareholders. Our study suggests that termination practices can potentially fill this gap by providing an implicit incentive for employees to act in the interest of the bank.

More broadly, our study relates to recent academic and regulatory interests in understanding cultural forces within the banking industry (Boissel et al. (2015), Thakor (2015), Pacelli (2016)). As noted by the Federal Reserve Bank, culture has surfaced as an important issue in recent years and is critical in "restoring public trust in the banking system and enhancing financial stability." Notably, the effects of culture can extend far beyond compensation and are also embedded in how individuals are "hired, rewarded, and fired" (Thakor (2015)). Our study provides evidence on how termination practices reflect culture within banks and influence employee behavior.

This paper develops as follows: Section 2 discusses the data and empirical tests. Section 3 provides univariate analyses. Section 4 provides our main results. Section 5 examines the mechanisms underlying our findings. Section 6 examines the effect of negative credit events and termination risk on bankers' lending standards. Section 7 concludes.

2 Data & Empirical Methodology

2.1 Data Sources & Sample Construction

We construct our sample by combining data from four primary sources. First, we collect information for all privately-placed debt contracts issued between 1994 and 2012 from LPC Dealscan. We restrict our sample to 93,073 loans that have available information regarding contract terms, such as markup and maturity. Next, we match borrowers to Compustat and retain only loan contracts in which firms have available fundamental information and exclude firms in financial and utility industries. This reduces our sample to 41,983 loans. Next, using the matched sample of borrowers and loan contracts, we collect information regarding bankers' identities from SEC filings. Requiring SEC data reduces our sample to 22,876 loan agreements.

Finally, we manually collect information regarding bankers' employment history from the online business networking service in order to identify the career paths of each bankers identified in the SEC dataset. We discuss the SEC and the networking service data in more detail below. After requiring the online networking data, our sample is reduced to 2,486 loan agreements extended by 1,436 unique bankers from 101 unique banks. For each banker in this sample, we expand her employment paths over time, thus constructing a banker-bank matched sample spanning the period of 1994–2014. The unit of observation is a banker-bank-year pair. For each observation, we construct an outstanding loan portfolio using all the loans issued by the banker from her bank of employment between the years of loan issuance and loan maturity. If a borrower in a banker's portfolio files for bankruptcy or defaults prior to loan maturity, we remove that loan from the portfolio. All observations for which we do not observe any outstanding loans for a given banker is removed from the sample. This leaves us a sample of 7,585 observations.

2.1.1 SEC Filings

We extract bankers identities following the procedure outlined in Gao et al. (2017b). Specifically, we first search SEC filings for all available loan documents. Loan documents are considered material public disclosures and are generally filed as Exhibits to firms' 8-K's, 10-Q's and 10-K's. In particular, we search for any public filing that contains an appended Exhibit 10 (which relates to "Material Contracts").

We next require the contract to contain either the word "loan" or "credit" followed by the word "agreement" in the title to ensure that the contract relates to a loan agreement, as opposed to other contracts (e.g., supply agreements, executive compensation agreements, etc.). We search all filings meeting this criteria in the 90-day window centered on the loan date observed in Dealscan. Doing so allows us to account for errors in the Dealscan dates.[4]

To identify bankers in charge of issuing each loan contract, we examine signature pages that are commonly attached to the end of loan agreements. Since most of these contracts are electronically filed, signatures can be identified by searching for the string "/s/", which indicates an electronic signature. We use the data surrounding the electronic signature string to extract

[4]As noted in Murfin (2012), Dealscan sometimes reports loan dates at a lag due to delays in the syndication process.

the name of the bankers, the bank in which she is employed, and her title. We then match bankers identities to their respective Dealscan loan. A unique feature of our data is that we can assign the individual bankers responsible for structuring a loan (and all of the loan's respective terms) to the loan observed in Dealscan.

2.1.2 Career Data from Online Networking Profiles

As we are interested in examining the impact of negative loan performance on bankers' career trajectories, we must further identify bankers' career movements. One limitation of the SEC documents is that they only indicate a banker's employer at the point in time in which the bankers issues a corporate loan. Thus, the SEC data does not capture the exact start date and end date of a banker's employment by a bank, the dates associated with promotions or demotions within the bank, or transitions between banks. Accordingly, we augment the SEC data with additional data from an online business networking service that provides detailed information on professionals' backgrounds and career paths. To do so, we match each banker observed in an SEC credit agreement to his or her respective online profile based on the bankers' first and last name, name of current employer, and date of employment.[5] This data increases the precision of our analysis by allowing us to more accurately identify bankers departure dates. Among the 1,436 unique bankers matched to their online profiles, we observe 720 departures (discussed in more detail below).

2.2 Variables of Interest

2.2.1 Negative Credit Events

We measure the performance of loans in a banker's portfolio using negative credit events. Specifically, we consider two types of negative credit events with increasing degrees of severity. The first category is rating downgrades, which indicate deterioration in a borrower's credit quality. While they do not present an imminent threat to banks' capital, they can generate reputation damage and may attract bank managers' attention (Gopalan et al. (2011), Bushman

[5]We define a lender based on the ultimate bank holding company level as of 2016. This definition removes the possibility of over-identifying banker exits due to bank mergers or intra-bank transfers between different divisions. Online profiles also contain more precise identification of parent banks than subsidiaries.

and Wittenberg-Moerman (2012)). We construct an indicator variable, *Downgrades*, that takes the value of one if at least one borrower to whom a banker originates a loan receives a downgrade from S&P in a given year, and zero otherwise.

In the second category, we examine more severe events, including default-related downgrades and corporate bankruptcies. Default ratings often trigger renegotiation between the borrower and its banks, capital losses to the banks, and even prompt banks to modify their lending standards (Roberts and Sufi (2009), Murfin (2012), Gao et al. (2017a)). Bankruptcies are likely to be the most costly credit event to banks, as they compete with other stakeholders of the firm (i.e., bondholders, suppliers, and employees) in retrieving capital (James (1995), Falato and Liang (2016)). We gather data regarding default ratings using S&P default categories ("D" or "SD"), and collect bankruptcy data from LoPucki bankruptcy database. Using these data sources, we construct an indicator variable, *Default*, that equals one if at least one borrower in a banker's portfolio begins receiving default ratings from S&P ("D" or "SD") or files for bankruptcy in a given year, and zero otherwise. Similar to downgrades, we only consider default events that take place before the maturity of the loan contract of interest.

Finally, we aggregate both types of credit events into one variable (*AllEvents*) that takes the value of one if a banker experiences at least one downgrade, default, or bankruptcy in her portfolio, and zero otherwise. To allow for a one-year window for bankers to move across institutions, we consider the occurrence of negative credit events occurring in the same year or previous year as the year of departure, i.e., year $t-1$ and year t.[6]

2.2.2 Exits

For each banker in our sample, we determine the first year and the last year of her employment at a given bank and span the banker's employment with the bank for all the years in between transition dates. This constitutes a base sample in which the unit of observation is a banker-bank-year pair. Using this sample, we define a dummy variable *Exit* that equals one if the year of observation is the last year that a banker works in her current bank, and zero otherwise.

[6] In untabulated analyses, we confirm that our results are robust to alternative windows, such as only year t, or three years prior to (inclusive) the year of departure, i.e., year $t-2$, year $t-1$, and year t.

2.3 Empirical Methodology

Our baseline model estimates banks' termination practices. Specifically, we examine the likelihood of a banker's departure occurring following a negative credit event within that bankers' loan portfolio using the following linear model:

$$Exit_{i,b,t} = \beta Credit\ Event_{i,b,t} + \Xi_b + \Lambda_i + \Delta_t + Controls_{i,t} + \epsilon_{i,b,t}, \tag{1}$$

where i represents a banker, b represents a bank, and t indicates the year of observation. The outcome variable *Exit* is a binary variable indicating that banker i exits bank b during year t. *Credit Event* is a binary variable denoting a negative credit event in year t or $t-1$ within the loan portfolio of employee i. In this estimation framework, we control for bank-fixed effects (Ξ_b) to remove time-invariant tendencies of banks to turn over their employees. We further control for banker-fixed effects (Λ_i) to remove the influence of bankers' latent preferences related to their career movement, such as risk appetite, personality, education, and other time-invariant characteristics. Finally, we include year-fixed effects (Δ_t) to control for macroeconomic conditions.

In this analysis, β measures the likelihood that a banker exits the bank following a negative credit event. This sensitivity should reflect lenders' termination practices. This construct is also similar to that examined in research examining turnover sensitivity to performance in other labor market contexts, such as CEOs (e.g., Bushman et al. (2010), Jenter and Kanaan (2015)). If banks generally enforce termination following negative credit events, we expect $\beta > 0$.

2.4 Control Variables

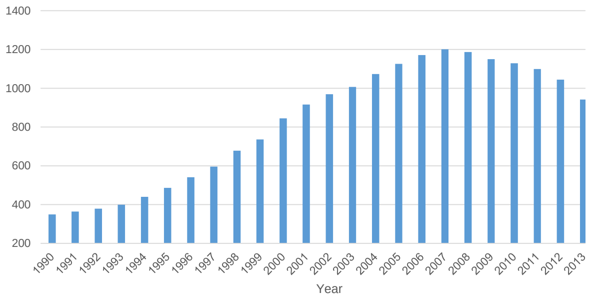
In addition to fixed effects, we also consider other time-varying features of a banker as well as her loan portfolio that could correlate with both her career movements and the performance of her loans. To start, we control for a banker's tenure, defined as the number of years that a banker has worked in a given bank. Bankers with longer tenures may be more likely to exit the bank. They are also likely to accumulate experience over time, which affects their performance.

Another factor that might affect the relationship between negative credit events and bankers departures is variation in a firm's demand for credit. Demand for credit presents a concern for our findings if the potential clients of a banker have similar demands for credit and bankers are more likely to depart a bank during periods of low loan origination. This explanation is important to consider given the descriptive evidence in Section 3 indicating that bankers specialize within industries. To account for this possibility, we control for average industry-level equity returns. Specifically, we identify the industries that a banker specializes in as the industries that the banker issues the highest number or amount of loans in her current bank of employment, and then compute the average equity returns of all the firms in those industries (*Industry Returns*). Relatedly, we also remove time-invariant features of the industry that could contribute to the credit quality or the demand for credit of firms in that industry. To do so, we control for industry-fixed effects in our baseline estimations.

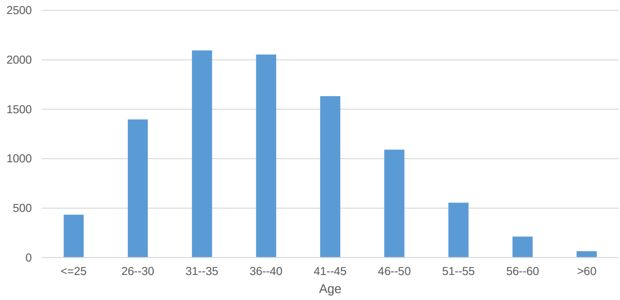
We further examine characteristics of the loans in a banker's portfolio, and control for important loan contract terms that could relate to loan performance. For example, if a banker correctly prices credit risk by issuing loans with high interest rate spreads, we should expect the banker to be less accountable for defaults. We thus control for the average spread of loans in a banker's portfolio, *Loan Spread.* Similarly, we also control for the average log amount of the loans in the portfolio (*Loan Size*) and the average maturity (*Loan Maturity*). In addition, we account for the size of a banker's portfolio using the total number of loans in her portfolio at each point in time (*#Loans in Portfolio*).

3 Univariate Analyses

Table 1 summarizes banker exits and negative credit events in our main sample. The data indicate several interesting trends. First, the average likelihood of a banker exiting an employer in our sample is 5.5%, indicating that exits are rare. Analyses of credit events over different horizons indicate that, in our sample, there is a 10% chance that a banker experiences a negative credit event in the current or the previous year. Not surprisingly, this statistic suggests that negative credit events are generally uncommon events. Across the two types of credit events, we find that downgrades are the most common type of events, as they have a 9% chance of occurring. In contrast, defaults and bankruptcies are highly unusual events, with an only 1.7% likelihood of occurring within the past two years.



(a) Bankers by year



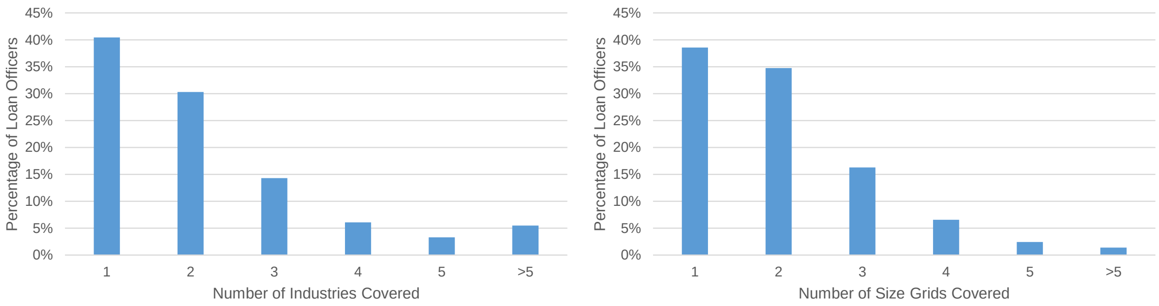
(b) Bankers by age

Figure 1. Composition of sample bankers. This figure presents the distribution of banker identified from the online networking platform. Panel (a) reports the number bankers identified each year. The horizontal axis indicates years, and the vertical axis indicates the number of bankers. Panel (b) reports the number of observations with bankers identified at each age range. The horizontal axis indicates banker age, and the vertical axis indicates the number of observations.

Table 1 About Here

As we rely on information from an online career networking service to construct the main sample, our sample naturally consists of bankers that are active on the online platform. As this networking service gains its popularity in the 2000s, we expect to observe more bankers in the years following 2000s compared to the 1990s. We also expect that our sample is more likely to contain younger bankers as these individuals are more likely to maintain an online presence. Figure 1 describes the composition of our sample bankers across years of observation and their age. Panel (a) reports the distribution of bankers by the year of observation, and Panel (b) represents the distribution of banker observations by their age, calculated based on the year of their college graduation. Consistent with our conjectures, the patterns suggest that there are a greater number of bankers in the 2000s than in the 1990s. Moreover, the majority of our sample bankers are younger, i.e., between the ages of 30 to 40.

Figure 2 examines the concentration of bankers' portfolios in terms of industry classification and size. In Panel (a), we count the number of industries covered by each banker and present a histogram illustrating the percentage of bankers covering a given number of industries (defined by two-digit SIC industries). Panel (b) illustrates the concentration of bankers' portfolios in terms of borrower size. Specifically, we classify the size of borrowers using the integer of the natural logarithm of their total assets and count the number of size buckets covered by bankers.



(a) Industry concentration **(b)** Size concentration

Figure 2. Concentration of bankers portfolios. This figure presents the percentage of bankers that focus on a certain number of industries or a certain number of borrowers' sizes. Panel (a) illustrates the percentage of bankers whose loan portfolios include firms belonging to a given number of industries (defined by two-digit SIC industries). Panel (b) illustrates the percentage of bankers whose portfolios include firms in a given number of size buckets. Size buckets are defined by integer levels of the natural logarithm of total asset values. In both panels, the vertical axis shows the percentage of bankers, and the horizontal axis indicates the number of industries (size buckets) covered by a banker.

The plot illustrates the histogram of bankers' size coverage using these buckets.

The pattern in Panel (a) suggests that 40% of the bankers within our sample exclusively extend loans to only one industry, while another 30% extend to only two different industries. Among our sample, less than 10% of bankers extend loans to five or more separate industries. These trends suggest that bankers appear to specialize in certain industries. We find similar evidence regarding specialization when we examine borrower size. As shown in the right panel of Figure 2, nearly 75% of bankers extend loans to one or two asset size buckets, while fewer than 5% extend to five or more different size buckets. The results suggest that bankers specialize within both industry and firm size.

Figure 3 further examines the rates of banker departures for the most prominent banks in our sample. The horizontal axis indicates the top ten lenders in declining loan volumes (from left to right). The columns represent the average number of bankers observed within a bank per year in our sample (left vertical axis). The solid line represents the likelihood of a banker exiting in a given year (right vertical axis). The figure indicates that banks with high deal volume such as Bank of America and Wells Fargo & Co. (Ross 2010) employ the most bankers. Interestingly, turnover rates appear to be rather consistent across the sample of banks. This suggests that, regardless of size, banks exhibit similar patterns of termination practices.

Figure 4 examines bankers' exit patterns. Panel (a) reports the distribution of the number and the exit ratio of bankers by year. The columns represent the number of bankers identified per

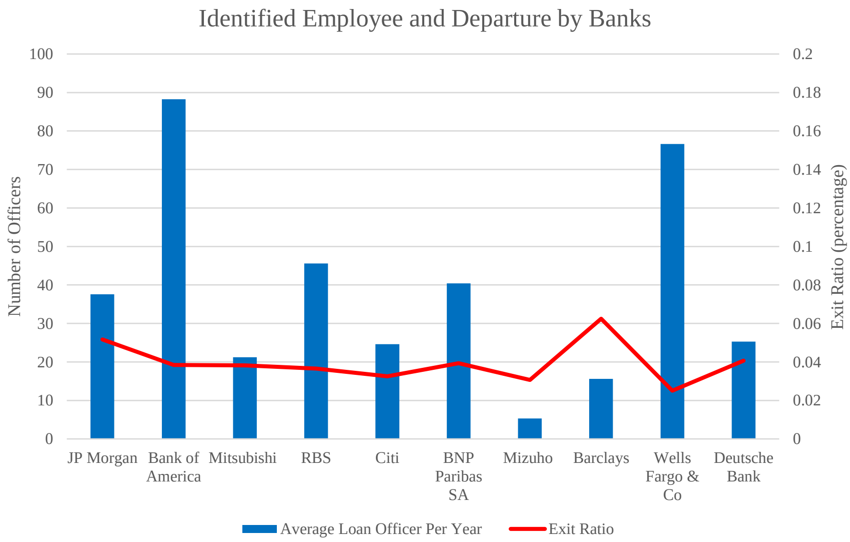
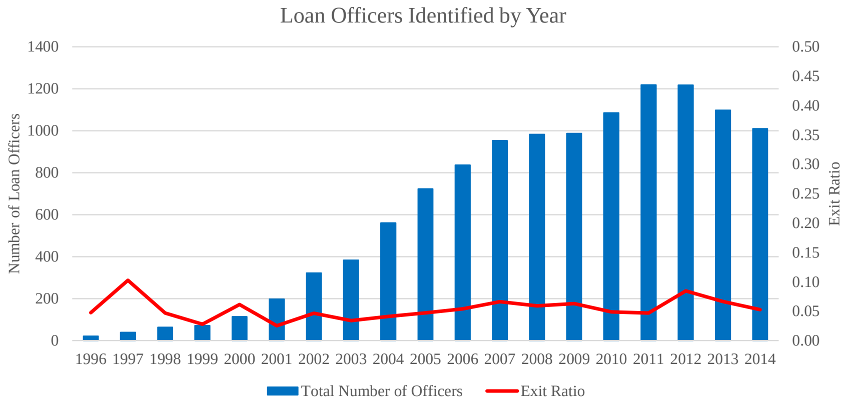


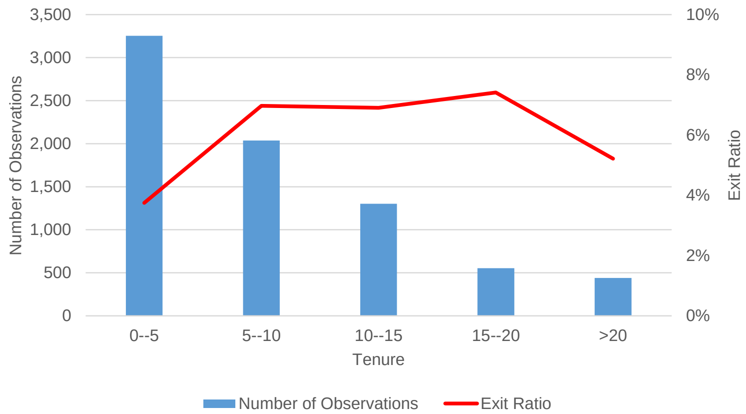
Figure 3. Banker departure by bank. This figure presents the number of bankers as well as the proportion of banker exits identified in the ten largest parent banks in our sample. The horizontal axis indicates the name of syndicated lenders in declining loan volumes (from left to right). The columns represent the average number of bankers identified per year for bank, and the solid line indicates the average proportion of bankers departing their current bank relative to the total number of bankers identified working at that bank over the whole sample period. The left vertical axis shows the total number of bankers identified, and the right vertical axis shows the proportion of bankers that depart the bank.

year, and the solid line indicates the proportion of bankers departing their current bank relative to the total number of bankers that year. The horizontal axis indicates years. Admittedly, our sample is smaller in early years due to limited coverage from both the SEC and the online business networking platform from which we collect our data. In recent years however, the number of bankers is rather static and generally ranges from 800 to 1,200. Exit ratios appear to peak in 1997 and 2012, and surprisingly, we find no evidence of increased exit rates during the 2008 Financial Crisis. We note that inferences from our analyses remain unchanged when we restrict the sample to more recent years (i.e., 2006–2015).

Panel (b) reports departure patterns by banker tenure. The columns represent the number of banker-year observations identified for each tenure range, and the solid line indicates the proportion of bankers that exit their current bank of employment relative to the total number of bankers in the same tenure range. The horizontal axis indicates tenure range. The majority of observations in our sample have a tenure of shorter than five years. However, a significant proportion of observations have a tenure of 5–15 years. On the other hand, very few bankers have tenures that exceed 20 years, suggesting that corporate banking positions tend to be attractive to individuals at earlier stages of their careers. Interestingly, there is an inverse-U-



(a) Exit by year



(b) Exit by tenure

Figure 4. Exit patterns of bankers. This figure presents the pattern of banker departure. Panel (a) reports bankers' departure by year. The columns represent the number of bankers identified per year, and the solid line indicates the proportion of bankers departing their current bank relative to the total number of bankers that year. Panel (b) reports departure pattern by bankers' tenure. The columns represent the number of banker-year observations identified for each tenure range, and the solid line indicates the proportion of bankers that exit their current bank of employment relative to the total number of bankers in the same tenure range. In each panel, the left vertical axis shows the number of bankers, and the right vertical axis shows the proportion of our sample bankers that leave their current affiliation.

shape relation between exit ratios and banker tenure. Exit ratio increases with tenure in the early stages of bankers' career, ranging from 4% during the first five years to around 7% as bankers work for over five years for a given bank. However, exit ratio later stabilizes at around 7% before decreasing to 5% as bankers work for more than two decades in the same bank. This suggests that career movement is limited in the early stages and later stages of one's career.

To sum up, our data indicates an average departure rate of roughly 5.5%, which is rather consistent across banks and over time. This estimate is also consistent with anecdotal evidence suggesting that turnover is infrequent in corporate finance departments. In the next section, we examine whether the past loan performance of bankers influences their turnover rate.

4 Baseline Results

4.1 Negative Credit Events & Departure

Table 2 presents results from estimates of equation (1). Columns (1) through (4) examine both types of negative credit events occurring in the current or prior year. In these tests, we gradually add control variables to our baseline estimation. Column (1) reports the result from regressing *Exit* on all credit events. Column (2) adds year- and bank-fixed effects. Column (3) further controls for banker tenure, banker-fixed effects, and borrowers' industry-fixed effects. Column (4) additionally controls for other characteristics of the banker's loan portfolio, including the average industry returns of portfolio borrowers, average loan spreads, size of the loans, and loan maturity. Finally, we control for the size of the loan portfolio using the number of loans outstanding. Results from this examination suggests that credit events are positively related to bankers' departure, with one additional event increasing the likelihood of departure by 2.4% (suggested by Column (4)).

TABLE 2 ABOUT HERE

In Table 3, we next examine whether the turnover-performance effect of a banker intensifies based on the severity of the event and the responsibility of the banker of interest. We first separate the credit events by type, as we expect that a banker that experiences a more severe credit event in her portfolio is more likely to be terminated. Columns (1) and (2) present the results from regressions of *Downgrade* and *Default* on banker exit, respectively. The results indicate that borrower defaults and bankruptcies generate much stronger effects. Having a borrower downgrade in the portfolio is associated with about 2.1% higher likelihood of departure, while a default event is associated with 6.4% higher departure likelihood, an effect that is three times as strong as that from downgrades.

In the next step, we consider bankers' roles in the syndicate, as the literature on relationship lending suggests that lead arrangers might play a greater role in syndicated lending decisions than participants. We thus construct two new measures of credit events. First, we examine lead arrangers' events. We thus define *Lead Events*, an indicator that equals one if a credit event occurs to a loan in which a banker is the lead arranger, and zero otherwise. Next, we define *Participant Events*, an indicator for negative credit events that occur to loans that a banker participated in. We expect that bankers should be more likely to face turnovers following downgrades or default of the loans they initiated as leaders than loans they only participated in. Accordingly, Column (3) examines the effect of leaders' credit events and Column (4) examines the effect of participants' credit events. Bankers are 3.4% more likely to face departure following a negative credit event arising from a loan that they originated as lead arrangers. In comparison, they are only 2% more likely to depart the bank following a negative credit event from the loan they participated in.

TABLE 3 ABOUT HERE

Overall, our base analysis provides evidence consistent with bankers who issue risky loans facing greater risk of turnovers by their bank of employment. Such practices also seem to intensity with the severity of the events and the responsibility of bankers for these credit events.

4.2 Robustness

Our results thus far provide evidence consistent with bankers' turnover following negative credit events. Given that we construct our main sample using SEC documents, it is not clear how firms' disclosure choices affect our inferences. In particular, some loan contracts may be omitted from SEC filings if they are deemed "not material" to the firm of interest. In this section, we consider the possibility that our sampling procedure may under-identify a banker's loan portfolio. We conduct two additional analyses to alleviate such concerns. First, we re-examine our base results on subsamples of firms who are more likely to voluntarily disclosure loan contracts. Second, we repeat our analyses on a backfilled sample, so as to expand the loan portfolios to all deals in the industry of specialization of a given banker.

4.2.1 Subsample Results

As the SEC requires firms to disclosure "material" contracts, we repeat our baseline analyses sampling on the set of firms that are likely to be under greater SEC scrutiny or whose loan contracts are more likely to be material to the shareholders, including larger firms and firms with greater loan-to-asset ratios. Additionally, negative credit events are likely to cluster in economic downturns, in particular, the 2008 financial crises. We thus sample on non-crises years to examine whether our results are driven by the 2008 financial crises.

Table 4 provides the results from our robustness analyses. In Column (1), we examine the sample of bankers whose portfolio borrowers have asset sizes above the sample median. In Column (2), we sample on bankers for whom the average portfolio borrowers have a loan-to-asset ratio that is above the sample median. Finally, in Column (3), we exclude the crises years 2008–2010 and examine the performance-exit relation for bankers in non-crises years. Our base results are robust to all of these sampling choices, where a negative credit event generates a similar economic magnitude to that from the baseline regression. Estimates from Column (2) suggest that the performance-turnover sensitivity of bankers are stronger for portfolio firms with high loan-to-asset ratio, that is, when bank loans are more likely to be economically important contracts for those borrowers.

Overall, these findings suggest that our results are unlikely to be driven by small firms, inconsequential loans, or the financial crisis.

TABLE 4 ABOUT HERE

4.2.2 Backfilled Sample

To further alleviate the concern that loan deals omitted by SEC documents could influence our findings, we construct a backfilled sample that assigns to a banker all of the loans issued by the same team in her bank. To start, we identify a banker's industry of specialization as the GIC industry in which the banker issues the highest number or largest amount of loans during her employment in a given bank. We next collect all of the loans in that GIC industry at the bank during the years that we can identify the banker is employed by that bank. We assign those loans to the banker. This procedure operates under the assumption that the banker works in a team that focuses on a given industry segment, and that she would have some influence over the lending decision made by the team. In the assignment process, we also only include the years that we can observe the banker having at least one outstanding loan in her portfolio.

Table 5 reports the results from the backfilled sample. Column (1) shows the univariate regression results. A credit event in a bank's loan portfolio is associated with about a 3% higher departure rate for bankers specializing in the same industry. Column (2) further controls for bank- and year-fixed effects. Column (3) controls for the tenure of the banker of interest, banker-fixed effects, and industry-fixed effects. Finally, Column (4) controls for characteristics of the loan portfolio of the banker. Our results persist across all of these specifications, suggesting that discretion in credit agreement disclosure is unlikely to affect our results.

TABLE 5 ABOUT HERE

4.3 Loan Officer Time-Varying Risk Preferences

Our findings thus far do not provide causal evidence to support our claims as negative credit events may not be exogenous and banker departures are potentially voluntary. By including banker-fixed effects in our analysis, we strengthen our claims as we demonstrate that the results are not driven by time-invariant differences across the banker population. However, it is still possible that the results are driven by unobservable, time-varying bankers characteristics, such as bankers' risk preferences. For example, over the course of her career, a banker may become more risk-tolerant, thus exerting less monitoring effort and seeking a new employer at the same time. This issue is difficult to address given the inherent challenges in measuring individual's risk preferences outside of an experimental setting (e.g., Cole et al. (2015)). Nonetheless, to alleviate this concern, we introduce a matching estimator approach that explicitly compares a banker facing a negative credit shock with a "counter-factual" banker who has participated in the same lending syndicate as the banker of interest, but has not experienced a negative credit shock. The method rests on the assumption that bankers who jointly issue the same loans are likely to have similar risk preferences.

In our analysis, we first identify the set of bankers experiencing a negative credit event as the treatment group. We define a control group as a separate set of bankers that have syndicated at least one loan with a treated bankers in the past five years, but have not experienced a negative credit event in the past. For each treatment-control match, we estimate the impact of the treatment (i.e., the negative credit event) on bankers' departure.

Table 6 provides the results from this analysis. We conduct the analysis on a sample of 1,142 banker-bank-year observations, consisting of 205 treated bankers and 500 matched control bankers. In Column (1) we estimate that a negative credit event results in treated bankers having a 3.6% greater likelihood of exiting the firm within a one-year window, compared to the control group. In Column (2), we include bank-, year-, and borrower industry-fixed effects, and estimate that treated bankers are 5.2% more likely to depart than are their matched control peers. These estimates are comparable and even stronger than those from the baseline analyses. In Column (3), we produce similar inferences after including banker-fixed effects and all control variables. This specification generates a stronger effect, i.e., a credit event is associated with a 7.7% greater likelihood of departure for the treated bankers compared to the control bankers. Overall, our matching procedure helps sharpen our inferences, suggesting that the observed departure-performance relation is unlikely to be driven by bankers' time-varying risk preferences.

Table 6 About Here

Taken together, our robustness analyses indicate that, even after controlling for certain sampling procedures and bankers' time-varying risk preferences, negative credit events still appear to be positively associated with bankers departures. The findings thus far provide strong evidence consistent with lenders enforcing termination practices that discipline inadequate screening and monitoring tendencies. In the next section, we further explore the economic mechanisms underpinning these findings.

5 Mechanisms

Having established a robust relationship between negative loan performance and banker departure, we next turn our attention to further exploring the mechanisms underpinning our findings. In particular, we conduct three sets of analyses. First, we confirm that banker turnover is consistent with termination, i.e., involuntary turnover. We next verify in our data that bankers benefit from originating a high volume of loans, which could present a conflicting incentive to risk management. Finally, we conduct cross-sectional analyses to verify that bankers' turnover-performance sensitivity is stronger when the bankers are less entrenched, and more liable to issuing loose credit terms.

5.1 Involuntary Turnover

Our findings indicate that bankers observe increased turnover rates following a negative credit event, and we argue that this result is consistent with bankers being terminated. This claim rests on the assumption that bankers are not voluntarily leaving banks after experiencing a negative credit event. To validate this claim, we further examine whether departures are associated with favorable or adverse career outcomes. Operating under the assumption that individuals are less likely to voluntarily move to a lower-ranked position than a higher-ranked position, we conjecture that negative credit events are more likely to be associated with adverse career outcomes for bankers.

To test this conjecture, we categorize bankers' career outcomes using online data detailing individuals' job transitions both inside banks and across banks. First, we define bankers' ranking within their institutions based on self-reported job titles available from the online business networking service. Each job title is then mapped to an occupation rank, as detailed in Appendix A. Given our focus on a narrow set of individuals (bankers in corporate banking), we can conduct this match from a relatively short list of possible job title terms. Using this classification, we define an internal promotion as an increase in the job title ranking for a given employee, and an internal demotion as a decrease in this ranking.[7]

We next consider the rankings of employers to categorize career movements across banks. In addition to considering job title changes, we rank all lenders in our sample according to the amount of loans they initiate in a given year, and consider the top five lenders as "prestigious." Movements from non-prestigious banks to prestigious banks are considered advancements in bankers' career. We thus define external promotion as cases in which a banker moves from a non-top-five ranked bank to a top-five bank, or a banker receives a higher title when she moves across similarly-ranked banks. Analogously, we define external demotion as cases in which a

[7] We assume that imprecise titles signal a lower position within the firm.

banker moves from a top-five bank to a non-top-five bank, or receives a lower title when moving to a bank with the same prestige.

We combine the above scenarios, and define *Promotion* as an indicator variable that takes the value of one if a banker moves to a larger bank, is internally promoted, or is promoted after moving to another bank, and zero otherwise. Note that we count as promotions the cases where a banker moves to a smaller bank in exchange for a higher title, or moves to a larger bank and settles for a lower title. We also define an indicator *Demotion* that equals one if a banker moves to a smaller bank where she receives a equally ranked or lower ranked title, or receives a lower ranked title in the current bank, and zero otherwise.

Table 7 presents the results from our analysis of promotions and demotions. In this set of analyses, we examine regressions of either promotion or demotion on negative credit events interacted with bankers departures. Within our sample, we identify 418 external job switches, in which 214 are promotions and 173 are demotions.[8] We also identify 204 instances of internal promotions. In Columns (1) through (3), the dependent variable is *Promotion*. The estimates suggest that, conditional on job transition, over half of the transitioning bankers in our sample face a promotion, as indicated by the loadings on *Exit*. Among the subset of exiting bankers with a recent credit event, we estimate a statistically significant decrease in the likelihood of promotion (i.e., an approximately 8% change).

In Columns (4) through (6), we re-examine these tests using *Demotion* as our dependent variable. In Column (4) we again exclude fixed effects and estimate that following a firm exit, about 40% of bankers face a demotion. Focusing on bankers that exit following a credit event, we find the likelihood of demotion increases by over 8%. We include year-, bank-, and borrower-industry-fixed effects in Column (5). We further control for banker-fixed effects together with other portfolio-level controls in Column (6). Across all specifications, we continue to estimate higher rates of demotion (around 6%–8%) for bankers that exit following a negative credit event. These results are economically meaningful and statistically significant, suggesting that negative credit events are associated with a higher demotion rate conditional on turnover.

<u>Table 7 About Here</u>

[8]The number of job switches are smaller than departures as we require the switching banker to transition to another Dealscan bank.

Overall, results from these tests help reinforce our claim that banker turnovers following negative performance are unlikely to be voluntary. Compared to average job transitions, bankers' turnovers following negative credit events are more likely to be demotions. Assuming that individuals do not voluntarily choose demotion, these findings add additional credence to our claim that negative credit events lead to bankers' termination.

5.2 Loan Origination and Promotion

Our next set of analyses verifies the positive incentives in place to promote higher volumes of loan origination. The Bureau of Labor Statistics reports that bankers are generally compensated with a fixed salary with added bonus for the volume of loans they issue. Given the competition among creditors and potential constraints to bankers' capacity of prospecting large numbers of high quality borrowers, these positive incentives towards volume may be in conflict with the disincentives against negative performance (see, e.g., Holmstrom and Milgrom (1991)). We verify in our data whether banks also place career incentives that reward origination. Specifically, we examine whether bankers that issue a large amount of syndicated loans receive promotions in the future. In this analysis, we focus only on internal promotions as our focus is on whether banks' internal incentive schemes reward loan origination.

For each banker, we measure the volume of loan origination as the log amount of loans she extended during the prior three years. We then regress internal promotion on bankers' past loan origination. Table 8 reports the results from this test. Columns (1) through (3) vary the inclusion of year-, bank-, and banker-fixed effects. Column (4) includes other portfolio-level control variables. The results indicate positive and significant associations between banker promotion and loan originations, suggesting that bankers originating higher volumes of loans are more likely to receive a promotion from their employers. In terms of economic magnitude, a one-standard-deviation increase in past loan origination is associated with a 3.5% increase in the probability of promotion. This estimate is economically significant compared to the 8% unconditional likelihood of promotion for the average bankers in our sample. Overall, these results confirm our conjecture that bankers face positive incentives to issue more loans.

TABLE 8 ABOUT HERE

5.3 Cross-Sectional Analyses

Our findings suggest that bankers are generally subject to greater risks of departure once they face negative loan performance in their portfolios. To verify the argument that bankers are subject to career incentives based on their lending behavior, we explore variations in bankers' position, experience, and lending standards.

We first explore variation in a banker's seniority. If a banker assumes a senior position, she is likely to be more entrenched in the institution and less likely removed from her position following a negative credit event. We thus partition the sample based on whether a banker has a title of "Director" or "Vice President," as those two types of titles account for over 80% of our sample. We expect the turnover-performance sensitivity to be stronger for bankers with "Vice President" titles. We next examine variation in a banker's tenure, i.e., the number of years that she has worked for a given bank. Bankers with long tenures are likely to be more entrenched, and meanwhile, the bank should be able to gather more information regarding a banker's quality. We thus conjecture that bankers with shorter tenures are more likely to exit the bank following negative credit events.

As the last step of our cross-sectional analyses, we verify whether bankers are less accountable for poor loan performance when they impose looser lending standards. To explore this variation, we calculate the risk-adjusted lending terms that a banker issues in a given year. For example, we calculate risk-adjusted covenants by first regressing the number of covenants on borrower characteristics, loan characteristics (such as loan size, type, and maturity) and bank-year fixed effects. We then take the residual from the regression and average across a banker's loan portfolio. We conduct similar tests for loan covenant strictness. The average level of "abnormal" covenants indicate the strictness of a banker's lending standard. If a banker generally issue loans with strict terms, such as imposing multiple covenants, and specifying tight covenant thresholds, we expect that the bankers may be less likely held accountable for the negative credit events in her portfolio.

We re-examine our baseline specification with the strictest set of controls using the aforementioned subsamples. Table 9 presents these results. Panel A reports the cross-sectional results related to bankers' position and tenure. Columns (1) and (2) report results for bankers that have director-level titles or VP-level titles, respectively. Consistent with our conjecture, bankers with VP-level titles face significantly higher risks of turnover following negative credit events, yet bankers with director-level titles face weaker and statistically insignificant turnover-performance sensitivity. Columns (3) and (4) present results for bankers with below or above 10 years of tenure in the bank of interest. The coefficients of *Credit Event* suggest that bankers with shorter tenures are 3% more likely to exit their banks of employment following negative credit events, yet bankers with over 10 years of experience barely face any risks of departure. Results from Panel A suggest that more experienced bankers are likely to be more entrenched in their institution and face weaker career incentives.

Table 9 About Here

Panel B reports cross-sectional results regarding bankers' lending standards. Columns (1) and (2) partition the sample based on whether a banker imposes below- or above-median number of loan covenants on their loans. Columns (3) and (4) partition the sample based on the risk-adjusted covenant strictness at issuance. Results from the subsample analyses suggest that bankers that issue loans with lax credit terms are more likely to depart the bank following negative credit events. In comparison, bankers that issue loans with strict covenants face very low risk of turnover, as indicated by the statistically insignificant coefficient of *Credit Event*.

Taken together, the results from our cross-sectional analyses lend further credence to our story that banks incentivize bankers by terminating them following negative credit events. Junior, less experienced bankers are more likely to exit their banks following credit events. Bankers who tend to grant lenient contract terms are also more likely to be "punished" for negative credit events occurring in their portfolios.

6 Implications for Lending Terms

The analysis above documents a robust relationship between negative credit events and bankers turnover. We argue that this relationship is consistent with banks imposing termination practices that reinforce proper monitoring. These practices may impose a threat of termination that can alter bankers' incentives and impact loan terms. In this section, we test this conjecture in two complementary frameworks. First, we estimate how negative credit events influence lending terms for bankers and their peers ex post. Second, we construct bank-specific measures of termination practices and examine whether these ex ante measures are correlated with lending standards.

6.1 Negative Credit Events and Lending Standards

We begin by directly examining whether a banker's own credit event affects her lending standards. In this set of analyses, we rely on loan characteristics from Dealscan database to create two measures of bankers' monitoring behaviors. First, we count the total number of covenants specified in the contract (*Covenants*). We then supplement this measure by computing the overall strictness of all covenants specified on loan contracts at initiation, following the procedures outlined in Murfin (2012) (*Strictness*). We then estimate the following model:

$$LendingStandard_k = \gamma_0 + \gamma_1 Credit\ Event_{i,b,t} + \gamma_2 FirmChar_{j,t} + \gamma_3 LoanChar_k + \Xi_b + \Gamma_{j,t} + \epsilon_k, \quad (2)$$

where k stands for a loan contract, and j stands for a borrower. The dependent variable, *LendingStandard*, is either *Covenants* or *Strictness*. We control for firm characteristics, including firm size, age, profitability, tangibility, market-to-book value, leverage, and an indicator for whether the firm receives a credit rating by S&P. We winsorize all continuous variables except for *Leverage* at the 5^{th} and 95^{th} percentiles. We limit *Leverage* to be within 0 and 1. We also include controls based on other observable lending characteristics, including *Spread*, the all-in-drawn loan spreads in basis points over LIBOR, *Maturity*, the number of months until the loan matures, and *LoanSize*, the natural logarithm of the dollar value of the loan contract (in $millions). Detailed variable definitions are available in Appendix A. In this set of analyses, we control for loan-type-fixed effects (term loan or revolver) and bank-fixed effects (Ξ_b) to remove time-invariant heterogeneities in contract terms across loan types and individual banks. We also include borrower industry-year-fixed effects ($\Gamma_{j,t}$) to control for industry dynamics that could affect loan terms. We classify industries using two-digit SIC codes.

We first focus our analysis on credit events related to the bankers of interest (*Credit Event (Own)*). Given that credit events increase the likelihood of termination, bankers may respond to this increased threat of termination by imposing stricter lending standards in the future. A banker may also update her beliefs about the likelihood of future credit events after experiencing one. In both cases, we expect that $\gamma_1 > 0$.

We extend this analysis to examine credit events occurring to the loan portfolios of peer bankers. We define peers as other bankers that are employed within the same bank as the bankers of interest during the same year (*Credit Event (Peer)*). Following negative credit events in peers' loan portfolios, a banker may update her belief about her own monitoring standards, the likelihood of a credit event, or the threat of termination inside the bank associated with credit events. In this case, the banker will adjust her lending standards upon seeing peer events, i.e., $\gamma_1 > 0$. On the other hand, if the banker does not draw any inference regarding the threat of termination or her monitoring standards from peer events, we should not see a significant coefficient for *Credit Event (Peer)*.

Table 10 summarizes the complete set of loan terms as well as control variables in the lending terms panel. The statistics indicate that approximately 23% of loans are written by bankers that have experienced a negative credit event in their loan portfolio within the prior three years. While it is relatively uncommon for a given loan to be issued by the same bankers who just experienced a credit event, it is much more common for a given loan to be issued by a banker whose peers recently experienced a credit event. Approximately, 72% of the loans originated in our sample are issued by bankers whose peers experienced a negative credit event in the past three years. We also examine the characteristics of loan contract features and borrowers within our sample. The average loan contract has an all-in-drawn spread of 194 basis points, matures in approximately 53 months, and amounts to nearly $20 million in value. In addition, the average loan contract carries two covenants, with a mean strictness of 0.45. Firms in our sample are relatively large and profitable, with an average asset base of $7.8 billion, age of 22 years, and profitability ratio of 13%. These firms also have high levels of tangible assets (average of 32%) and moderate leverage ratios (average of 33%). Finally, approximately 69% of the firms in the sample have bond ratings.

TABLE 10 ABOUT HERE

Table 11 reports the results from estimates of equation (2). In Columns (1) and (4) we focus on only the negative credit events arising from a banker's own portfolio (i.e., *Credit Event*

(Own)). In Columns (2) and (5), we instead focus on the credit events occurring to the portfolios of peer bankers (*Credit Event (Peer)*). In Columns (3) and (6), we consider both the credit events of a banker and her peers. The results suggest that credit events can influence lending terms. A banker's own credit event is associated with approximately 0.13 more covenants and a 2% increase in strictness, after controlling for peer credit events. Moreover, peer bankers' credit events also seem to influence the number of covenants issued, yet the magnitude of such an influence is smaller than that from bankers' own events. Specifically, peer credit events are associated with about 0.09 more covenants. These are economically meaningful effects, compared to the average number of covenants (2) specified on a loan contract. The effects of peer credit events on covenant strictness, however, are negligible. Finally, we note that the coefficient on a banker's own credit event changes marginally as we control for peer bankers' credit events. This suggests that a banker's own performance and the performance of her peers elicit different information for the banker's lending standards.

TABLE 11 ABOUT HERE

6.2 Bank-specific Termination Risk and Lending Standards

Our second set of analyses examines the extent to which risk management practices, or the "termination culture," differ across banks. In this set of analyses, we evaluate how the cross-sectional variation in the propensity of terminating bankers influences lending standards within each bank. The assumption that banks have time-invariant risk management practices is consistent with recent research revealing that bank cultures and risk preferences are slow to change (Fahlenbrach et al. (2012), Ellul and Yerramilli (2013), Thakor (2015), Pacelli (2016)).

We conduct our estimation in two separate stages. In the first stage, we estimate a bank-specific tendency of terminating bankers following a negative credit event. We thus estimate equation (1) for each bank in our sample, obtaining a bank-specific coefficient, $\hat{\beta}_b$. Higher values of $\hat{\beta}_b$ imply that negative credit events are more likely to induce bankers turnovers at bank b. In the second stage, we evaluate whether a higher termination tendency is associated with stricter

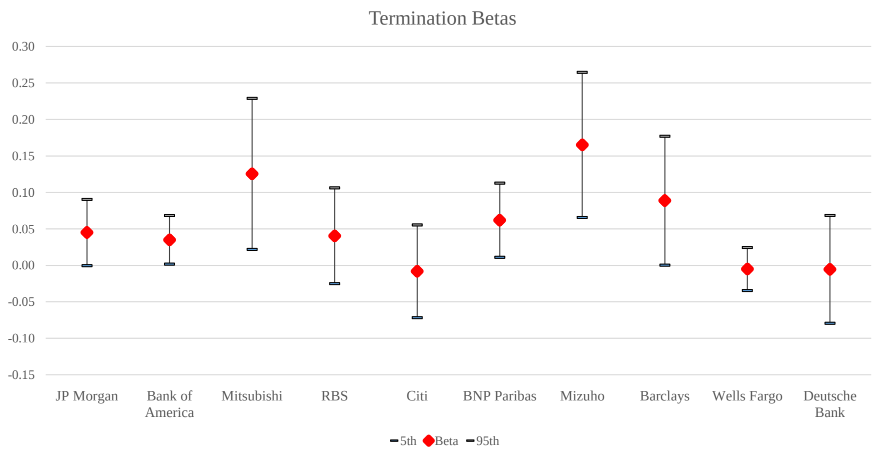


Figure 5. Bank-specific termination risk. This figure reports the estimated termination risk for each of the ten largest banks in our sample. The diamond-shaped markers show the estimated betas for each bank, and the flat markers at the top and bottom of each column show the 5^{th} and 95^{th} interval of these estimated betas.

lending standards within the bank. Specifically, we consider the framework:

$$LendingStandard_k = \gamma_0 + \gamma_1 \widehat{\beta}_b + \gamma_2 FirmChar_{j,t} + \gamma_3 LoanChar_{j,t} + \Gamma_{j,t} + \epsilon_k, \qquad (3)$$

Where $\Gamma_{j,t}$ indicates industry-fixed effects. We predict that $\gamma_1 > 0$, suggesting that bankers working in a bank with a high-termination risk environment also institute stricter lending standards (i.e., imposing more covenants and stricter covenants in their loan contracts).

The first stage estimation yields considerable cross-sectional variations in bank-level termination tendencies, which we visualize in Figure 5. This plot illustrates the estimated termination betas, $\widehat{\beta}_b$, for the largest banks in our sample. We present both the estimated level as well as the 10% confidence interval for the estimation. Though the majority of large banks in our sample have positive and significant termination betas, there is also notable heterogeneities across banks. For example, bankers employed by Mitsubishi and Mizuho appear to face higher termination risk than bankers employed by Citibank and Wells Fargo. This suggests that risk-management policies vary even among the largest syndicate lenders.

We next evaluate how termination practices within a bank impact loan terms. Table 12 reports consistent evidence that termination policies are positively correlated with both the number of covenants and covenant strictness. Recall that we measure termination practices as the likelihood of bankers turnovers occurring within two years following a negative credit event. Therefore, our results suggest that a ten percent increase in termination beta increases the number of covenants by 0.054 (Column (1)) and the strictness by 0.07 (Column (2)). These magnitudes are economically meaningful considering that the average loan in our sample carries two covenants, and has a strictness of 0.45. These results are robust to controlling for borrower characteristics and observable differences in other loan terms.

Table 12 About Here

Overall, the findings from our lending terms analyses suggest that termination practices play an important role in disciplining bankers behavior. Following a credit event, a banker increases both the number of covenants and the strictness of loan covenants. We find a similar, though smaller, effect when a banker's peer experiences a credit event in her portfolio. Next, after developing a measure of bank-specific termination risk, we find that banks with stricter termination policies are associated with more and stricter covenants. These findings lend further support to our argument that career incentives are effective in influencing bankers' contracting tendencies.

7 Conclusion

In this study, we examine the role of career incentives in disciplining bankers' lending standards and influencing loan performance in the market for corporate loans. We construct a comprehensive dataset tracking the career paths of bankers in the U.S. corporate lending market through the period of 1994–2014. We find that negative loan performance, as proxied by negative credit events such as defaults, bankruptcies, and rating downgrades, increases the likelihood of bankers' departing their place of employment. Negative credit events provide a more informative signal to bank managers when information asymmetries are more pronounced (i.e., within larger, more complex banks and among less experienced bankers). Importantly, we find that banks' termination practices effectively incentivize bankers to raise their lending standards by imposing a greater number of covenants as well as stricter covenant terms on future loans.

Our study adds to the growing literature studying bankers incentives under asymmetric information inside banks (see, e.g., Cole et al. (2015), Agarwal and Ben-David (2015)). It also sheds light on the role of culture in disciplining risk-taking in financial institutions (Fahlenbrach et al. (2012), Ellul and Yerramilli (2013)). Overall, our results generate policy implications for both financial institutions and the agencies that regulate them. We document that terminating bankers responsible for poor performance appears to be a common practice in the corporate banking industry. This practice effectively disciplines bankers' lending behavior, reducing credit risk exposure for the banks. Within the regulatory arena, evaluating the termination policies within a bank can serve as an additional ex-ante measure of risk exposure across the cross-section of banks.

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Appendix A Variable Definitions

Exit and credit events

- *Exit*: A dummy variable that equals one if the current year of observation is the last year that a banker works at a given bank (excluding 2016), and zero otherwise.
- *Downgrade*: A dummy variable that equals one if at least one borrower of a banker experiences a downgrade by S&P in a given year, and zero otherwise.
- *Default*: A dummy variable that equals one if at least one borrower of a banker receives a default rating from S&P ("D" or "SD") or files for bankruptcy in a given year, and zero otherwise.
- *AllEvents*: A dummy variable that equals one if at least one borrower of a banker experiences a downgrade, default, or bankruptcy in a given year, and zero otherwise.

Firm characteristics

- *Size*: Log(Total Asset (AT))
- *Age*: Firm age, based on its first appearance in Compustat database
- *Profitability*: Operating income (OIBDP)/AT
- *Tangibility*: Property, Plant, and Equipment (PPENT)/AT
- *Market to Book*: (Stock price (PRCC)*shares outstanding (CSHO) + AT - Book value of equity (CEQ))/AT
- *Leverage*: (Long-term Debt (DLTT) + Current Debt (DLC))/ AT
- *Rated*: A dummy variable that equals one if the firm has a bond rating, zero otherwise

Loan characteristics

- *Spreads*: All-in-Drawn loan spread over LIBOR
- *Covenants*: Total number of covenants specified in the loan package
- *Strictness*: Covenant strictness at loan issuance, calculated using the method described in Murfin (2012)
- *Maturity*: Loan maturity in months
- *Amount*: Log of total loan amount (in dollars)
- *Loan Spread*: The average level of All-in-Drawn loan spreads across all the outstanding loans in a banker's portfolio in a given year
- *Loan Maturity*: The average level of loan maturity across all the outstanding loans in a banker's portfolio in a given year
- *Loan Size*: The average level of log loan amount across all the outstanding loans in a banker's portfolio in a given year
- *#Loan in Portfolio*: The number of outstanding loans in a banker's portfolio in a given year

Job Title Ranking

- *Rank 7*: Chief Executive Officer and President
- *Rank 6*: Other Chief Officers (primarily Chief Financial Officer)
- *Rank 5*: Director, Department Head, Treasurer, Partner, Principal
- *Rank 4*: Senior/Executive Vice-President, Assistant Treasurer, Assistant Director
- *Rank 3*: Vice-President
- *Rank 2*: Assistant Vice-President, Manager
- *Rank 1*: Analyst, Associate, Lender, Officer, Banker, Underwriter

Appendix B Influence of Bankers

A large literature on syndicated loans suggests that loan terms are not based merely on hard information (Engelberg, Gao, and Parsons (2012), Karolyi (2016)). In this way, syndicated loans differ from small commercial loans where pricing is driven primarily by computerized bank algorithms (Rajan, Seru, and Vig (2015), Cortes, Duchin, and Sosyura (2016)). To confirm that the bankers in our sample are indeed responsible for structuring the credit agreements, we conduct two sets of analyses. This is a necessary concern in our analysis: incentives have no impact when the employee has limited responsibility in the particular task. First, we show that the past experience of a banker influences her current terms, even after controlling for other loan characteristics. Second, we conduct fixed effects analyses following Gao et al. (2017) and Herpfer (2017) to examine whether bankers' fixed effects explain more variation than the fixed effects of their banks.

In the first analysis, we evaluate the correlation between loan spreads over the banker's career. If current deals are influenced by the banker's past deal terms (also known as anchoring), then spreads will be correlated. Assuming bankers are randomly assigned, then we can test for anchoring by regressing the current loan spread on a past spread; however, if assignment is not random and bankers specialize in a type of loan/borrower, then spreads will be correlated even in the absence of anchoring. While it is possible to include controls in the analysis, there is always the possibility that unobservable characteristics between borrowers explain any correlation. Instead, we require a banker characteristic that is likely exogenous to the current borrower. To overcome the identification issue, we develop a new framework similar to that introduced by Dougal, Engelberg, Parsons, and Van Wesep (2015). In it, we examine how past global spreads influence current individual loan spreads. Specifically, we evaluate how the global spread during the banker's most recent loan can influence her current loan spread for a different firm. Underlying this strategy is the possibility that bankers actively/passively depend on past loans to price current loans and fail to acknowledge differences in the interest rate environment. In this way, our methodology is similar to research acknowledging how past experiences impact current financial decisions (Malmendier, Tate, and Yan (2011)). For comparison, we also test how the most recent loan spread offered by the bank correlates to the current spread offered by a related firm. Underlying this framework is the assumption that loan spreads are priced by the bank (rather than the particular employee).

More specifically, we examine whether past experiences of a banker should shape the deal terms she underwrites today. We do so regressing the spreads on a loan contract on the spreads of previous loan deals issued by the corresponding banker observed on the loan deal. We define two variables of interest: First, we identify the spread on the previous syndicated loans originated by the same banker in a prior year, *Prior Spread (Banker).* We next proxy for the overall lending standards when a banker issued a previous loan. Specifically, we define *Predicted Prior Spread (Banker)* as the average spread for loans of the same type (term loans, revolvers, or other) originated in the same calendar year as the last loan issued by the banker. For comparison, we repeat the analyses at the bank level, thus defining *Prior Spread (Bank)* and *Predicted Prior Spread (Bank)*. *Prior Spread (Bank)* is the spread on the last syndicated loan originated by a given bank in the borrower's industry and in a prior year. *Predicted Prior Spread (Bank)* is the average spread of loans of the same time, originated by that bank in the borrower's industry and in a prior year. In calculating all variables, we remove previous loans that are extended to the same borrower. In excluding these loans, we seek to examine whether personal or institutional memories can shape future lending decisions.

Table B1 reports the results. Columns (1) through (4) examine the effect of bankers' experience on loan spreads. Columns (1) and (2) examine the effect of bankers' experience from the last loan and Columns (3) and (4) examine the effect of bankers' experience regarding the lending standards. Results from these tests suggest that the loan spreads from a banker's previous deals are significantly and positively associated with the pricing terms on the current loan. A one-basis-point increase from a previous deal is associated with around a 7%-basis-point increase in the spread on the current loan. These results suggest that the experience from previous deals are likely to shape a banker's lending behavior in the future. Columns (5) through (8) examine the effect of banks' past experience on loan spreads. Prior experience of a bank seems to have much weaker and insignificant bearings on current lending terms.

In the next analyses, we repeat the AKM analyses following Abowd, Kramarz, and Margolis (1999) on our sample of banker-bank-loan pairings. In this analyses, we compare the explanatory power of bankers and subsidiary banks they are employed by, so as to allow greater variations explained by banks. After imposing the connectedness requirement of the AKM analyses, we are able to identify 293 movers and 1,044 stayers in a sample of 284 connected subsidiary banks. Table B2 reports the results. Panel A reports the incremental R^2s explained by officer and fixed effects estimated from a traditional fixed effect model. Panel B presents results from the AKM method. Similar to our baseline analyses, the traditional fixed effect model reveals that bankers explain a larger portion of the variation in loan contract terms and loan performance than do banks. Their explanatory power ranges from 20% for loan spreads to 37% for borrower default. The AKM analyses generate similar magnitudes. Banker effects are both statistically and economically significant. The AKM results suggest that the R^2 explained by bankers are 3.5 times as much as that explained by banks for loan spreads, and over 7 times as strong as banks for borrower default.

Overall, this preliminary evidence suggests that bankers indeed have an important economic effect on loan contract terms and loan performance. It is reasonable to attribute poor loan performance to these bankers.

Table B1. Effect of bankers through prior experience

This table shows the effects of loan spreads issued by a given banker in previous loans she issued on the spreads of her current loans. All regressions control for bank-year-fixed effects. *Prior Spread (Banker)* is the spread for the last syndicated loan originated by the banker in a prior year. *Predicted Prior Spread (Banker)* is the average spread for loans of the same type (term loans, revolvers, and other) originated in the same calendar year as the last loan issued by the banker. *Prior Spread (Bank)* is the spread for the last syndicated loan originated by that bank in the borrower's industry and in a prior year. *Predicted Prior Spread (Bank)* is the average spreadof loans of the same time, originated by that bank in the borrower's industry and in a prior year. All regressions control for bank-year-fixed effects.

Dep. Var.: *Spread*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prior Spread (Banker)	0.1185***	0.0630**						
	(5.31)	(2.84)						
Predicted Prior Spread (Banker)			0.1092***	0.0671**				
			(3.79)	(2.53)				
Prior Spread (Bank)					0.0612***	0.0167		
					(3.52)	(1.09)		
Predicted Prior Spread (Bank)							0.0265	0.0120
							(0.95)	(0.48)
Loan Size		-28.4117***		-28.6857***		-29.8342***		-29.8503***
		(-12.78)		(-12.70)		(-14.04)		(-13.91)
Loan Maturity		10.5384		11.3623		2.2234		2.2329
		(1.47)		(1.64)		(0.29)		(0.29)
#Loans in Portfolio		0.3339		0.2563		-0.9711*		-0.9787*
		(0.40)		(0.31)		(-2.09)		(-2.11)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type FE	No	Yes	No	Yes	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	3,701	2,724	3,701	2,724	3,822	3,165	3,822	3,165
Adjusted R^2	0.4503	0.6144	0.4425	0.6126	0.3359	0.5286	0.3329	0.5284

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B2. Bankers' effects from fixed effect models

This table reports the effects of bankers and banks in explaining loan spreads and loan performance. The sample includes all banker-bank pairs in our sample. Panel A reports the incremental R^2s explained by banker and bank fixed effects estimated from a traditional fixed effect model. For each dependent variable, we report adjusted and unadjusted R^2s from estimating the regression model with controls (same in Table 11), with loan officer fixed effects, with bank fixed effects, and with both loan officer and bank fixed effects. The incremental R^2s are computed using unadjusted R^2s. Panel B reports the results from the AKM analyses (introduced in introduced in Abowd et al. (1999)). The estimation is implemented using the Stata command "felsdvreg" as described in Cornelissen (2008). The unit of observation is a syndicated loan, bank, and banker. The rows for "F-test on FE" report the F-statistics of the null hypothesis that the estimated banker or bank fixed effects are jointly zero. "# Movers" reports the number of bankers that changed affiliation in the sample, "# Stayers" reports the number of bankers that do not change affiliation, and "# Banks" is the total number of banks in the sample.

Panel A Traditional Fixed Effect Model

Regression:		Adjusted R^2	Unadjusted R^2	Incremental R^2	
Dep. Var.: *Loan Spreads*					
(a)	Baseline	52.04%	52.84%		
(b)	Baseline + Bankers FE	63.41%	73.59%	(b) − (a)	20.74%
(c)	Baseline + Subsidiary Bank FE	57.47%	60.54%	(c) − (a)	7.69%
(d)	Baseline + Both FE	64.13%	75.23%	(d) − (c)	14.70%
Dep. Var.: *Default*					
(a)	Baseline	22.62%	23.93%		
(b)	Baseline + Bankers FE	45.33%	60.54%	(b) − (a)	36.62%
(c)	Baseline + Subsidiary Bank FE	27.56%	32.79%	(c) − (a)	8.87%
(d)	Baseline + Both FE	49.08%	64.86%	(d) − (c)	32.07%
Dep. Var.: *Downgrades*					
(a)	Baseline	25.72%	26.97%		
(b)	Baseline + Bankers FE	46.45%	61.35%	(b) − (a)	34.38%
(c)	Baseline + Subsidiary Bank FE	30.84%	35.83%	(c) − (a)	8.86%
(d)	Baseline + Both FE	48.38%	64.37%	(d) − (c)	28.54%

Panel B AKM Estimation

Dep. Var.:	(1) *Loan Spreads*	(2) *Default*	(3) *Downgrades*
R^2 explained			
Banker FE	22.68%	38.97%	36.14%
Subsidiary Bank FE	6.57%	5.32%	4.22%
Bankers FE/Bank FE	3.45	7.32	8.56
F-test on FE			
Banker FE	1.83***	2.66***	2.41***
Subsidiary Bank FE	1.53***	2.63***	1.84***
# Movers	293	293	293
# Stayers	1,044	1,044	1,044
# Subsidiary Banks	284	284	284
Unique banker-bank pair	1,691	1,691	1,691
Controls	Yes	Yes	Yes
Banker FE	Yes	Yes	Yes
Subsidiary Bank FE	Yes	Yes	Yes

*** p <0.01, ** p <0.05, * p <0.1

Table 1. Summary Statistics
This table shows the summary statistics for measures of bankers departure and negative credit events. The sample spans over the period of 1994–2014.

Variable	N	Mean	Std Dev.
Exit	7,585	0.055	0.228
Downgrade	7,585	0.090	0.286
Default	7,585	0.017	0.129
AllEvents	7,585	0.100	0.300

Table 2. Credit events and bankers' exits
This table examines the relation between loan performance and the likelihood of banker exit. The dependent variable is *Exit*, an indicator variable that equals one if an officer exits a bank in a given year, and zero otherwise. The sample spans through the period of 1994 to 2014, and includes 1,436 officers and 101 banks. *Credit Event* is defined as *AllEvents*. It accounts for events occurring in both the year of observation and the previous year. t-statistics are shown in parentheses.

Dep. Var.: *Exit*	(1)	(2)	(3)	(4)
Credit Event	0.0280***	0.0234***	0.0231**	0.0236**
	(3.21)	(2.65)	(2.43)	(2.50)
Banker Tenure			0.0202***	0.0239***
			(9.22)	(9.57)
Industry Return				0.0008
				(0.04)
Loan Spread				-0.0000
				(-0.10)
Loan Size				-0.0023
				(-0.33)
Loan Maturity				-0.0122
				(-1.07)
#Loans in Portfolio				-0.0008
				(-1.01)
Year FE	No	Yes	Yes	Yes
Bank FE	No	Yes	Yes	Yes
Banker FE	No	No	Yes	Yes
Industry FE	No	No	Yes	Yes
Observations	7,585	7,585	7,585	7,585
Adjusted R^2	0.0014	0.0277	0.3625	0.3797

*** p-value<0.01, ** p-value<0.05, * p-value<0.10

Table 3. Severity of events and bankers' role

This table examines the relation between loan performance and the likelihood of banker exit based on the severity of credit events and the role of bankers in the syndicates. The dependent variable is *Exit*, an indicator variable that equals one if an officer exits a bank in a given year, and zero otherwise. Column (1) shows the results where credit events are defined as downgrades, and Column (2) show the results where credit events are defined as defaults or bankruptcies. Column (3) presents the results for *Lead Events*, an indicator that equals one if a credit event occurs in a banker's portfolio when she is the lead arranger of that loan. Column (4) presents the results for *Participant Events*, an indicator for a credit event occurring to a loan that a banker participated in. All events are measured in both the same year and the previous year as the year of exit. All regressions control for year-, bank-, banker-, and borrower-industry-fixed effects, t-statistics are shown in parentheses.

Dep. Var.: *Exit*	(1)	(2)	(3)	(4)
Credit Event defined by:	*Downgrade*	*Default*	*Lead Events*	*Participant Events*
Credit Event	0.0209**	0.0635***	0.0338**	0.0183
	(2.17)	(2.90)	(2.04)	(1.60)
Banker Tenure	0.0239***	0.0239***	0.0238***	0.0240***
	(9.59)	(9.59)	(9.54)	(9.61)
Industry Return	0.0014	-0.0029	0.0008	-0.0004
	(0.06)	(-0.13)	(0.04)	(-0.02)
Loan Spread	-0.0000	-0.0000	-0.0000	-0.0000
	(-0.09)	(-0.11)	(-0.10)	(-0.09)
Loan Size	-0.0024	-0.0017	-0.0024	-0.0022
	(-0.35)	(-0.24)	(-0.34)	(-0.32)
Loan Maturity	-0.0121	-0.0120	-0.0117	-0.0120
	(-1.05)	(-1.04)	(-1.02)	(-1.05)
#Loans in Portfolio	-0.0008	-0.0007	-0.0008	-0.0007
	(-0.98)	(-0.83)	(-0.96)	(-0.84)
Year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Banker FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	7,585	7,585	7,585	7,585
R-squared	0.3796	0.3800	0.3795	0.3794

*** p-value<0.01, ** p-value<0.05, * p-value<0.10

Table 4. Robustness analyses

This table examines the relation between loan performance and the likelihood of banker exit in subsamples. Column (1) shows results for a subsample of bankers whose portfolio borrowers have asset sizes are above sample median. Column (2) examines a sample of bankers whose average portfolio borrowers have a loan-to-asset ratio that is above sample median. Column (3) examines the performance-exit relation in non-recession years (excluding 2008–2010). All regressions control for year-, bank-, banker-, and borrower-industry-fixed effects. t-statistics are shown in parentheses.

Dep. Var.: Exit Sample	(1) Large Firms	(2) High Loan-to-Asset	(3) Non-Recession Years
Credit Event	0.0224*	0.0367**	0.0276**
	(1.77)	(2.23)	(2.57)
Banker Tenure	0.0258***	0.0318***	0.0199***
	(6.43)	(6.40)	(7.37)
Industry Return	-0.0239	0.0159	0.0011
	(-0.68)	(0.41)	(0.04)
Loan Spread	-0.0001	0.0001	0.0001
	(-0.80)	(1.11)	(1.13)
Loan Size	0.0121	-0.0106	0.0026
	(1.07)	(-0.69)	(0.34)
Loan Maturity	0.0167	-0.0331	-0.0188
	(0.97)	(-1.18)	(-1.47)
#Loans in Portfolio	-0.0010	-0.0018	-0.0010
	(-1.09)	(-0.66)	(-1.21)
Year FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Officer FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	3,549	3,282	5,859
R-squared	0.4447	0.3969	0.4524

*** p-value<0.01, ** p-value<0.05, * p-value<0.10

Table 5. Negative credit events and bankers exit: Backfilled sample
This table examines the relation between loan performance and the likelihood of banker exit using a backfilled sample. In this sample, we assign to a banker who is employed by a given bank all loans issued by that bank to the banker's primary GICS industry during the year of her employment. Primary industries are defined as an industry where the banker issued the higher number of loans or greatest amount of loans. The dependent variable is *Exit*, an indicator variable that equals one if an officer exits a bank in a given year, and zero otherwise. The sample spans through the period of 1994 to 2014, and includes 1,436 officers and 101 banks. Credit Events are defined as all events, including downgrades, defaults, and bankruptcies. All events are measured in both the same year and the previous year as the year of exit. t-statistics are shown in parentheses.

Dep. Var.: *Exit*	(1)	(2)	(3)	(4)
Credit Events	0.0301***	0.0253***	0.0194**	0.0198**
	(3.09)	(2.65)	(2.04)	(2.07)
Banker Tenure			0.0201***	0.0238***
			(9.11)	(15.55)
Industry Return				0.0017
				(0.07)
Loan Spread				-0.0000
				(-0.14)
Loan Size				-0.0025
				(-0.38)
Loan Maturity				-0.0120
				(-0.98)
#Loans in Portfolio				-0.0007
				(-1.44)
Year FE	No	Yes	Yes	Yes
Bank FE	No	Yes	Yes	Yes
Banker FE	No	No	Yes	Yes
Industry FE	No	No	Yes	Yes
Observations	7,585	7,585	7,585	7,585
Adjusted R^2	0.0023	0.0283	0.3625	0.3797

*** p-value<0.01, ** p-value<0.05, * p-value<0.10

Table 6. Negative credit events and bankers exit: Syndicate matched sample
This table examines the relation between loan performance and the likelihood of loan ocer departure using a matched sample. The dependent variable is *Exit*, an indicator variable that equals one if an ocer exits a bank in a given year, and zero otherwise. The sample spans through the period of 1994 to 2014 and includes only ocers with a negative credit events (Treated) and other ocers that have worked on at least one loan with the treated ocer in the past ve years but have not experienced any negative credit event since then (Control). The matched sample includes 670 loan ocers, 193 of whom are treated ocers and 477 are control loan ocers. *t*-statistics are shown in parentheses.

Dep. Var.: *Exit*	(1)	(2)	(3)
Treat (Credit Event = 1)	0.0356**	0.0520***	0.0768***
	(2.04)	(2.70)	(3.13)
Banker Tenure			0.0244**
			(2.48)
Industry Return			-0.1474*
			(-1.80)
Loan Spread			-0.0005*
			(-1.82)
Loan Size			-0.0017
			(-0.06)
Loan Maturity			-0.0188
			(-0.47)
#Loans in Portfolio			-0.0007
			(-0.46)
Year FE	No	Yes	Yes
Industry FE	No	Yes	Yes
Bank FE	No	Yes	Yes
Officer FE	No	No	Yes
Observations	1,102	1,091	811
Adjusted R^2	0.0038	0.1029	0.4947

*** p-value<0.01, ** p-value<0.05, * p-value<0.10

Table 7. Negative credit events, promotion and demotion

This table reports the effect of past loan performance on the turnover and career paths of loan ocers. The sample spans through the period of 1994 to 2014. Within this panel, there are 853 events classied as job switches, among which 269 events are indicate promotion (154 cases) or demotion (115 cases). We also identify 120 cases where loan ocers are internally promoted or demoted. The dependent variable in Columns (1) through (3) is *Promotion*, an indicator variable that equals one if a loan ocer moves to a larger bank, is internally promoted, or is promoted after moving to another bank. The dependent variable in Columns (4) through (6) is *Demotion*, an indicator variable that equals one if a loan ocer moves to a smaller bank, is internally demoted, or is demoted after switching jobs. Robust t-statistics are shown in parentheses.

Dep. Var.:	*Promotion*			*Demotion*		
	(1)	(2)	(3)	(4)	(5)	(6)
Credit Event	0.0007	0.0009	-0.0028	0.0000	-0.0003	0.0025
	(0.12)	(0.15)	(-0.40)	(0.00)	(-0.07)	(0.49)
Exit	0.5223***	0.5196***	0.5066***	0.3976***	0.3984***	0.4196***
	(60.71)	(59.77)	(49.20)	(60.77)	(60.25)	(55.81)
*Credit Event*Exit*	-0.0864***	-0.0858***	-0.0612**	0.0846***	0.0930***	0.0558***
	(-3.80)	(-3.73)	(-2.34)	(4.89)	(5.31)	(2.92)
Banker Tenure			-0.0009			0.0005
			(-0.49)			(0.34)
Industry Return			0.0023			0.0032
			(0.13)			(0.25)
Loan Spread			-0.0000			-0.0000
			(-0.28)			(-0.13)
Loan Size			-0.0022			0.0034
			(-0.50)			(1.05)
Loan Maturity			-0.0001			0.0006
			(-0.01)			(0.10)
#Loans in Portfolio			0.0000			-0.0001
			(0.08)			(-0.23)
Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	Yes	No	Yes	Yes
Bank FE	No	Yes	Yes	No	Yes	Yes
Officer FE	No	No	Yes	No	No	Yes
Observations	6,963	6,960	6,865	6,963	6,960	6,865
Adjusted R^2	0.3716	0.3852	0.5353	0.3985	0.4111	0.5989

*** p-value<0.01, ** p-value<0.05, * p-value<0.10

Table 8. Loan origination and internal promotion

This table reports the effect of the dollar value of loan originations on the career paths of loan ocers. The sample spans through the period of 1994 to 2014. The dependent variable is *Internal Promotion*, an indicator variable that equals one if a loan ocer's rank increases at the current employer, and zero otherwise. Robust t-statistics are shown in parentheses.

Dep. Var.: *Internal Promotion*	(1)	(2)	(3)	(4)
Loan Origination	0.0007*	0.0009**	0.0012**	0.0010*
	(1.82)	(2.11)	(2.43)	(1.69)
Banker Tenure			0.0003	-0.0006
			(1.39)	(-0.45)
Industry Return			0.0049	0.0048
			(0.46)	(0.41)
Loan Spread			-0.0000*	-0.0000
			(-1.86)	(-0.43)
Loan Size			-0.0022	-0.0011
			(-1.41)	(-0.36)
Loan Maturity			0.0055	0.0005
			(1.63)	(0.09)
#Loans in Portfolio			-0.0002	-0.0003
			(-0.60)	(-0.75)
Year FE	No	Yes	Yes	Yes
Bank FE	No	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes
Officer FE	No	No	No	Yes
Observations	6,963	6,960	6,960	6,865
Adjusted R^2	0.0005	0.0133	0.0229	0.2277

*** p-value<0.01, ** p-value<0.05, * p-value<0.10

Table 9. Cross-sectional analyses
This table examines the subsample results in the relation between loan performance and the likelihood of banker exit. In Panel A, we partition the sample by bankers' seniority. Column (1) shows results for bankers with a title of "Vice President," Column (2) shows results for bankers with "Director" titles, Column (3) shows results for bankers with fewer than 10 years of tenure, and Column (4) shows results for bankers with more than 10 years of tenure. Panel B partitions the sample based on the initial terms of loan contracts. Columns (1) and (2) partition the sample based on whether the number of covenants specified on the contracts is above or median sample median. Columns (3) and (4) partition the sample based on the strictness of covenants across a banker's portfolio loans. In both panels, the dependent variable is *Exit*, an indicator variable that equals one if an officer exits a bank in a given year, and zero otherwise. *Credit Events* are defined as all events, including downgrades, defaults, and bankruptcies. All events are measured in both the same year and the previous year as the year of exit. All regressions control for year-, bank-, banker-, and borrower-industry-fixed effects. t-statistics are shown in parentheses.

Panel A. Bankers' Seniority

Partition by:	*Seniority*		*Tenure*	
	Vice President	Directors	<10 Years	≥10 Years
Dep. Var.: *Exit*	(1)	(2)	(3)	(4)
Credit Event	0.0269**	0.0144	0.0318***	0.0006
	(1.96)	(1.10)	(2.82)	(0.03)
Banker Tenure	0.0278***	0.0220***	0.0308***	0.0537***
	(8.03)	(6.05)	(10.86)	(3.33)
Industry Return	-0.0236	0.0293	0.0153	-0.0132
	(-0.75)	(0.87)	(0.57)	(-0.30)
Loan Spread	-0.0000	-0.0000	-0.0001	0.0002
	(-0.38)	(-0.05)	(-1.64)	(1.21)
Loan Size	-0.0098	0.0083	0.0072	-0.0132
	(-0.99)	(0.83)	(0.82)	(-0.95)
Loan Maturity	0.0002	-0.0195	-0.0233	-0.0012
	(0.01)	(-1.19)	(-1.58)	(-0.05)
#Loans in Portfolio	-0.0024**	0.0007	-0.0011	-0.0017
	(-2.08)	(0.60)	(-1.20)	(-0.71)
Year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Banker FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	4,332	3,253	4,914	2,671
Adjusted R^2	0.4143	0.3744	0.4424	0.4486

Panel B. Loan Terms

Sample Partitioned By	*#Covenants*		*Strictness*	
	Low	High	Low	High
Dep. Var.: Exit	(1)	(2)	(3)	(4)
Credit Event	0.0375***	0.0008	0.0327**	0.0002
	(2.73)	(0.06)	(2.26)	(0.01)
Banker Tenure	0.0246***	0.0276***	0.0242***	0.0281***
	(6.57)	(6.30)	(6.25)	(5.73)
Industry Return	-0.0186	0.0301	0.0464	-0.0524
	(-0.58)	(0.84)	(1.39)	(-1.38)
Loan Spread	0.0001	-0.0000	-0.0000	-0.0000
	(0.48)	(-0.01)	(-0.20)	(-0.30)
Loan Size	-0.0058	-0.0018	-0.0090	-0.0053
	(-0.52)	(-0.14)	(-0.81)	(-0.36)
Loan Maturity	-0.0190	-0.0048	-0.0206	-0.0363
	(-1.08)	(-0.24)	(-1.14)	(-1.56)
#Loans in Portfolio	-0.0013	-0.0005	-0.0007	-0.0011
	(-1.23)	(-0.28)	(-0.54)	(-0.85)
Year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Banker FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	4,077	3,508	3,888	2,977
Adjusted R^2	0.4265	0.4585	0.4295	0.4699

*** p-value<0.01, ** p-value<0.05, * p-value<0.10

Table 10. Sample characteristics for loan contracts
This table shows the summary statistics for measures of firm characteristics and loan contract terms. The sample spans over the period of 1994–2014. All continuous variables except *Leverage* are winsorized at the 5th and 95th percentile. *Leverage* is restricted to the 0–1 range.

Variable	N	Mean	Std Dev.	P25	Median	P75
Variables of Interest						
Covenants	15513	1.9840	1.2958	1	2	3
Strictness	12636	0.4484	0.3737	0.0779	0.3939	0.8223
Credit Event (Own)	15513	0.2309	0.4214	0	0	0
Credit Event (Peer)	14442	0.7221	0.4480	0	1	1
Firm Characteristics						
Size	15513	7.8613	1.4617	6.9000	7.7676	8.8403
Age	15513	22.3843	16.9518	9	16	34
Profitability	15513	0.1250	0.0799	0.0831	0.1184	0.1633
Tangibility	15513	0.3235	0.2587	0.1007	0.2619	0.4975
M/B	15513	1.6108	0.7818	1.1688	1.4266	1.7937
Leverage	15513	0.3384	0.2025	0.1954	0.3125	0.4439
Rated	15513	0.6899	0.4625	0	1	1
Loan Characteristics						
Spreads	15513	194.4486	137.7318	100	175	250
Maturity	15513	52.7827	19.2663	46	60	60
Amount	15513	19.5867	1.2985	18.8262	19.6734	20.4356

Table 11. Negative credit events and loan contract terms

This table examines the effect of a banker's own past negative credit events (as well as those of her peers) on future loan contracting terms. The sample spans through the period of 1994 to 2014, containing only bankers with peers. Columns 1 through 3 examine the effect of credit events on the number of covenants imposed on future loan contracts extended by the bankers (*Covenants*). Columns 4 through 6 examine the effect of these credit events on the covenant strictness at loan issuance (*Strictness*). Peers are defined as all other bankers that work in the same bank during a given year. All regressions include bank-, year-, and bankers-fixed effects. Robust t-statistics are shown in parentheses.

Dep. Var.:	*Covenants*			*Strictness*		
	(1)	(2)	(3)	(4)	(5)	(6)
Credit Event (Own)	0.1255***		0.1252***	0.0218***		0.0207***
	(5.97)		(5.88)	(3.74)		(3.51)
Credit Event (Peer)		0.0888***	0.0893***		0.0001	0.0002
		(3.10)	(3.12)		(0.02)	(0.03)
Size	-0.2009***	-0.2004***	-0.2028***	-0.0440***	-0.0433***	-0.0438***
	(-16.33)	(-16.01)	(-16.22)	(-12.71)	(-12.29)	(-12.45)
Age	0.0002	0.0005	0.0004	-0.0000	-0.0000	0.0000
	(0.30)	(0.66)	(0.58)	(-0.01)	(-0.00)	(0.05)
Profitability	0.2118	0.1602	0.1825	-0.6257***	-0.6061***	-0.6017***
	(1.50)	(1.11)	(1.27)	(-14.91)	(-14.10)	(-14.00)
Tangibility	-0.2041***	-0.2251***	-0.2237***	0.0185	0.0127	0.0136
	(-3.00)	(-3.25)	(-3.23)	(0.91)	(0.61)	(0.65)
M/B	-0.0198	-0.0175	-0.0158	-0.0551***	-0.0553***	-0.0550***
	(-1.35)	(-1.18)	(-1.07)	(-13.28)	(-13.13)	(-13.05)
Leverage	0.3739***	0.3688***	0.3623***	0.5437***	0.5405***	0.5396***
	(6.25)	(6.05)	(5.95)	(31.53)	(30.71)	(30.68)
Rated	0.1136***	0.1324***	0.1239***	0.0328***	0.0330***	0.0320***
	(4.21)	(4.84)	(4.53)	(4.22)	(4.19)	(4.05)
Spreads	0.0004***	0.0004***	0.0004***	0.0007***	0.0007***	0.0007***
	(4.84)	(4.58)	(4.54)	(23.53)	(24.52)	(24.50)
Maturity	0.0053***	0.0052***	0.0053***	0.0006***	0.0006***	0.0006***
	(9.96)	(9.52)	(9.69)	(3.73)	(3.56)	(3.73)
Amount	-0.0491***	-0.0460***	-0.0479***	-0.0035	-0.0019	-0.0022
	(-4.40)	(-4.04)	(-4.21)	(-1.14)	(-0.61)	(-0.70)
Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,513	14,800	14,800	12,636	12,000	12,000
Adjusted R^2	0.5666	0.5485	0.5496	0.6845	0.6789	0.6792

*** p-value<0.01, ** p-value<0.05, * p-value<0.10

Table 12. Negative credit events, termination threat and lending standard
This table reports the effect of termination threat on bankers' lending standards. The sample spans through the period of 1994 to 2014. The dependent variable in column 1 is *Covenants*, the number of covenants specified in a loan contract. The dependent variable in column 2 is *Strictness*, the covenant strictness defined according to Murfin (2012). The variable of interest is the estimated bank-specific termination tendency, $\widehat{\beta}_b$, estimated from bank-by-bank regressions as in Eq. 1. All regressions include industry-year-fixed effects and loan type-fixed effects. Robust t-statistics are shown in parentheses.

	(1)	(2)
Dep Var:	*Covenants*	*Strictness*
$\widehat{\beta}_b$	0.9205***	0.1630**
	(4.22)	(2.30)
Size	-0.2126***	-0.0453***
	(-13.41)	(-8.72)
Age	0.0011	0.0005
	(1.22)	(1.64)
Profitability	-0.6131***	-0.6320***
	(-3.26)	(-10.14)
Tangibility	-0.2148**	0.0072
	(-2.39)	(0.24)
M/B	0.0266	-0.0700***
	(1.44)	(-11.31)
Leverage	0.5948***	0.5152***
	(7.40)	(19.22)
Rated	0.1386***	0.0126
	(3.97)	(1.09)
Spreads	0.0008***	0.0008***
	(6.47)	(18.15)
Maturity	0.0044***	-0.0002
	(6.76)	(-0.90)
Amount	-0.0494***	-0.0041
	(-3.78)	(-0.97)
Loan Type FE	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
People FE	Yes	Yes
Observations	10,391	8,228
Adjusted R^2	0.6874	0.7156

*** p-value<0.01, ** p-value<0.05, * p-value<0.10