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Credit and Punishment: Are Corporate Bankers Disciplined for Risk-Taking?

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We examine whether bankers face disciplining consequences for structuring poorly performing corporate loans. We construct a novel data set containing the employment histories and loan portfolios of a large sample of corporate bankers and find that corporate credit events (i.e., downgrades, defaults, bankruptcies) increase banker turnover. The effect is pronounced when bankers issue loans with loose terms or experience severe losses. Credit events prompt bankers to adopt stricter future risk management practices, such as offering restrictive covenant packages. Overall, our findings are consistent with banks disciplining employees as a means to manage their own risk exposure. (*JEL* G20, G21, G30, J24, J63)

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The large-scale loan losses associated with the global financial crisis triggered an extensive discussion about how banks should manage credit risk. A growing concern is that nonexecutive employees, such as bankers and traders, have a material influence on banks' risk exposure, and that their risk-taking activities contributed to the crisis (Kashyap, Rajan, and Stein 2008; Kashyap 2010;

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Federal Reserve 2011; Ellul and Yerramilli 2013). It is thus crucial to understand whether and to what extent banks discipline employee risk-taking.

Existing evidence on this issue often suggests a lack of disciplining in the banking sector. For example, the media and prominent economists have accused banks of not holding bankers accountable for their actions and have advocated for stronger consequences.[1] Relatedly, concurrent research finds no evidence that bankers faced any career-related costs following the housing crisis (Griffin, Kruger, and Maturana 2019). Recent studies also indicate that bank managers or shareholders focus on profit and neglect risk exposure (e.g., Baron and Xiong 2017; Fahlenbrach, Prilmeier, and Stulz 2017), suggesting that employees may not be punished for risk-taking.[2] The importance of this debate warrants a systematic examination of whether bankers face consequences for failing to manage credit risk.

This study provides large-scale evidence on the extent to which corporate bankers face disciplining consequences for structuring poorly performing corporate loans (i.e., loans that experience ratings downgrades, bankruptcies, or defaults). We also examine whether such events prompt bankers to issue more stringent lending terms in the future. We focus on the corporate loan market for several important reasons. First, corporate loans account for a large portion of banking assets and represent a significant risk management concern for regulators.[3] Second, risk management represents a key responsibility for corporate bankers, as they are tasked with not only originating new loans but also designing covenants that facilitate monitoring after loan issuance. Third, the corporate loan market provides a unique opportunity for examining how banks respond to employee risk-taking. Our data allow us to track individual bankers' lending standards, loan performance, and career paths over two decades, and construct a sample containing \$1.8 trillion of loans issued by over 1,400 individuals employed by major U.S. banks. This granularity of data allows us to shed light on the extent to which banks discipline employees who have an economically meaningful effect on risk exposure.

Our empirical analyses are grounded in a canonical career concerns framework (e.g., Gibbons and Murphy 1992; Gibbons 1996; Holmström 1999). In applying this framework to our setting, one may consider the bank as the principal whose objective is, in part, to manage risk exposure. Bankers represent the agent, who may be unable or unwilling to manage risk according to the bank's preferences as they benefit from originating new loans, potentially at

1 Prominent critics of banks' disciplining practices include George Akerloff and Joseph Stiglitz, who argue in favor of imprisoning bankers involved in predatory lending practices (Washington 2010).

2 In other words, it is possible that employees issue risky loans under the directives of bank managers or shareholders, in which case employees may not be held responsible for generating risk exposure.

3 The Shared National Credit Program produces annual reports detailing risk management concerns in this market (https://www.federalreserve.gov/supervisionreg/snc-archive.htm). Consistent with high risk-taking being a concern, the review frequently highlights analogous concerns regarding bank loan quality. For example, the 2015 report noted "continuing gaps between industry practices and the expectations for safe and sound banking."

the cost of loan quality. Given that the bank cannot directly observe a banker's ability or efforts, it can learn about a banker's type from "credit events" (i.e., ratings downgrades, defaults, or bankruptcies arising in the banker's portfolio).[4] By terminating bankers responsible for structuring troubled loans, the bank can remove employees with misaligned risk preferences and motivate greater risk management efforts due to heightened career concerns.

Our primary analyses examine one key empirical implication of this framework by assessing whether bankers' turnover rates increase in the year immediately following the revelation of a credit event. Our results indicate that the occurrence of a credit event is associated with an approximately 50% increase in the relative likelihood that a banker departs his or her bank. The estimations take into account a banker's portfolio characteristics, borrower characteristics, banker-, bank-, and borrower industry-year fixed effects. Notably, the results are robust to controlling for various benchmarks of credit risk, including the prevailing credit spreads charged on "comparable" loans and the performance of comparable loans (Murfin and Pratt 2018). In these specifications, we classify comparable loans with similar characteristics issued during the year prior to origination of the loan of interest, including those in the same maturity range and extended to borrowers in the same industry, ratings category, and distance-to-default threshold. Benchmarking bankers' credit risk exposure against the perceived and realized credit risk of comparable loans helps us generate inferences regarding how banks evaluate bankers' risk-taking relative to prevalent lending standards in the market. Overall, our results suggest that bankers face disciplinary consequences for generating risk exposure.

In cross-sectional analyses, we find that the relation between credit events and banker turnover becomes more pronounced when the credit event is more severe, indicating that banks are stricter on bankers that generate costlier events. This includes cases when loans result in defaults and bankruptcies, when the banker is the lead arranger of the loan, and when the bank retains a high allocation of the loan. In addition, bankers face greater turnover rates when they issue loans with more lax covenants than other bankers in the same institution. This finding is consistent with banks targeting bankers who did not exercise prudent risk management practices. Collectively, our evidence suggests that banks remove bankers who are responsible for inducing credit risk exposure.

Our evidence thus far suggests that banks impose disciplining consequences on bankers that issue loans that fail. A natural follow-up question is whether the external labor market also disciplines credit events. Our next set of analyses explores this question by assessing bankers' career outcomes following credit events. We focus on a sample of moving bankers and track their next place of employment. We construct a variety of measures reflecting the quality of the banker's next job (e.g., the size and prestige of the institution, rank and position,

[4] This is because lending decisions are based, in part, on soft, nonverifiable information possessed by the banker only (Berger and Udell 2004; Petersen 2004).

quality of life). We then analyze whether exiting bankers experience differential career outcomes (i.e., find better or worse-quality jobs) depending on the occurrence of a credit event. Our results indicate no statistically significant differences in the career outcomes of bankers experiencing a credit event. Although exiting bankers do not appear to take less desirable jobs following a credit event, there is also no evidence that they move to better positions or institutions. One possible explanation for the lack of evidence on downward movements is that outside banks are unable to determine how at fault the banker is given the reliance on soft, private information in corporate lending (Berger and Udell 2004; Petersen 2004).

Another important implication of the career concerns framework is that heightened turnover risk should promote higher lending standards. Our next set of analyses assesses this implication. We examine how credit events occurring in a banker's portfolio relate to the banker's future lending standards, as reflected in the number of covenants and strictness of covenants. These analyses control for comparable lending terms, borrower characteristics, and include banker fixed effects, thus allowing us to assess how bankers change their lending standards following periods of heightened turnover rates. Consistent with expectations, our results indicate that bankers set stricter covenant packages in deals they originate following credit events. We also gauge disciplining intensity at the bank level by estimating turnover credit event sensitivities (bank turnover betas) for each bank in our sample. Higher turnover betas suggest that banks respond to credit events by terminating employees to a greater extent and thus reflect more stringent risk management practices. We find that bankers working in high-beta banks issue loans with more covenants and stricter covenants, a pattern that is consistent with career concerns motivating more stringent lending standards. Overall, our findings provide evidence in support of the prediction that the threat of discipline deters risk-taking by employees.

Next, we examine why bankers still take risks despite facing disciplining consequences. We propose that bankers face a conflicting incentive to generate new deals, potentially at the cost of loan quality. To provide some context on this point, we analyze a large sample of job postings for corporate banker positions and find that many postings require bankers to expand the bank's client base while simultaneously analyzing and managing credit risk.[5] More formally, we examine the relationship between loan volume and promotion. Our results indicate that recent lending volume is associated with career promotions (i.e., a rise in rank at the current bank or a new position of at least equal rank at a larger bank). This finding supports our claim that bankers face conflicting incentives to grow their loan portfolio, potentially at the cost of loan quality.

[5] This analysis is based on data collected from Burning Glass Labor Insights. Burning Glass is a leading platform for job market data analytics and maintains a database containing nearly all online job vacancy postings in the United States (Deming and Kahn 2018; Hertzel et al. 2008).

We conclude by assessing various alternative explanations for our findings. For example, deteriorating market conditions can lead to both mass layoffs and loan failures. We note, however, that our results are robust to including industry-year or bank-year fixed effects and that the effects we document are just as strong in periods of economic expansion. Another alternative explanation is that credit events are the result of "bad luck," suggesting that banks may inefficiently terminate unlucky bankers. This argument, however, does not explain why turnover is more pronounced among high-risk loans and bankers that issue lax covenants. In addition, we assess the possibility that bankers entering the industry at different points in time may have varying tendencies of switching jobs. This explanation is unlikely to drive our results, as our findings remain robust after controlling for various types of cohort effects. We further consider the possibility that heightened career concerns do not motivate bankers to exercise stricter lending standards. Instead, credit events may simply help banks learn about how to improve their overall lending process. One important piece of evidence that contradicts this explanation is that changes in a banker's lending standards are not correlated with credit events arising from the banker's *colleagues'* portfolios, but are only correlated with credit events arising from the banker's *own* portfolio. Finally, we acknowledge that our data does not allow us to completely rule out the possibility that bankers voluntarily depart following credit events. This concern can be partially alleviated by the fact that turnover is generally costly (Greenwald 1986; Jacobson, LaLonde, and Sullivan 1993; Şahin et al. 2014), and such costs should be particularly high for bankers if they lose clients in the process (Herpfer 2018). In addition, we find no evidence to indicate that bankers obtain better positions after credit events, thus making it less likely that they voluntarily depart. Overall, our results are most consistent with the argument that banks discipline risk-taking.

Our study contributes to a growing line of research examining how financial institutions and labor markets discipline individuals (Chevalier and Ellison 1999; Griffin, Kruger, and Maturana 2019; Ellul, Pagano, and Scognamiglio 2020; Egan, Matvos, and Seru 2019). Several related studies examine the career consequences associated with misconduct for different types of financial services employees. Our study is closely related to Griffin, Kruger, and Maturana (2019), who find limited evidence that residential mortgage backed securities (RMBS) bankers faced heightened turnover after the financial crisis. In contrast, our results suggest that corporate bankers are punished for aggressive lending practices. Griffin, Kruger, and Maturana (2019) suggest that one important reason for their inability to find a disciplining effect is that banks did not want to acknowledge wrongdoing in the period of intense scrutiny following the financial crisis. Our study does not focus on the effect of the financial crisis, but instead examines how banks respond to less high-profile events occurring during noncrisis periods. Notably, a bank's response to such events is less likely to be influenced by regulatory pressure or media attention. Our results suggest that managing employee risk-taking is an important priority for banks, as credit events lead to turnover and bankers tightening their lending standards.

Second, our study also relates to that of Egan, Matvos, and Seru (2019), who examine the role of discipline in the financial advisory market, where the primary regulatory concern is investor protection. In contrast to Egan, Matvos, and Seru (2019), we focus on bank lending, where the central regulatory objective is preventing systemic risk (Allen and Herring 2001). Understanding whether bankers are disciplined for loan failures is important in its own right as it sheds light on banks' risk management practices. High levels of risk-taking can be detrimental to a bank's safety and stability (Adrian and Shin 2010; Shleifer and Vishny 2011) and can potentially reduce a bank's ability to fund economic growth (Chodorow-Reich 2014). Our inferences also differ from those of Egan, Matvos, and Seru (2019) in one additional dimension: While Egan, Matvos, and Seru (2019) find that advisors are often repeat offenders, we find that bankers generally tighten their lending standards after experiencing credit events. By demonstrating that credit events can influence the supply and terms of credit, our results furthermore have implications for the extensive academic literature examining the determinants of firms' access to credit (e.g., Graham, Li, and Qiu 2008; Hertzel et al. 2008; Lin et al. 2011; Hertzel and Officer 2012).

Finally, our study also contributes to the literature examining risk management and bank risk exposure. Since the financial crisis, regulatory and academic interest in understanding the causes of risk management failures has grown. Prior studies largely focus on the role of top-level managers in mitigating risk (Fahlenbrach and Stulz 2011; Ellul and Yerramilli 2013; Cheng, Raina, and Xiong 2014). We contribute to this literature by examining how banks manage risk-taking among mid-level employees in the corporate banking sector. This is an important concern given that these individuals are tasked with growing responsibilities in increasingly complex financial markets (Federal Reserve 2011).

1. Theoretical Framework and Empirical Prediction

To motivate our analysis, we rely on the canonical career concerns framework (e.g., Gibbons and Murphy 1992; Gibbons 1996; Holmström 1999) and discuss its primary empirical prediction. We also describe the key economic mechanisms of this framework in the Internet Appendix (Section IA.1) using a stylized model. In applying the career concerns framework to our setting, the bank (i.e., the employer) represents the principal, and bankers (i.e., the employees) represent the agent.[6] The bank wants to limit risk exposure in its lending activities, but bankers may be unable or unwilling to manage risk accordingly. This is because bankers have heterogeneous screening and

[6] We assume that the interests of banks and managers are aligned with those of shareholders.

monitoring abilities and exert varying degrees of effort. In addition, information asymmetry exists within the bank such that the bank cannot perfectly observe bankers' actions. As bankers' abilities and efforts influence loan outcomes (ratings downgrades, defaults or bankruptcies), these "credit events" serve as a useful signal for the bank to learn about the banker's ability and effort.[7] By raising the threat of termination following a credit event, the bank can remove bankers with low perceived ability and more importantly, motivate all bankers to exert greater efforts to manage risk.[8] As such, termination can reduce the bank's future risk exposure.

Our primary prediction is that banks will impose disciplining consequences on bankers who incur credit events in their portfolios. This conjecture relies on several assumptions. First, there must exist information asymmetry between bank managers (or shareholders) and bankers. Second, bankers should face some constraint or competing incentive that prevents them from minimizing risk in the first place. Third and finally, credit events must be costly to the bank and therefore the potential occurrence of these events indicates risk exposure. We discuss each of these assumptions in turn.

First, our prediction depends on a large degree of information asymmetry between the bank manager and bankers, which prevents the bank from observing bankers' risk management abilities or efforts. This friction arises from the role that soft information plays in the lending process. When prospecting, screening and monitoring borrowers, bankers often build long-standing relationship with their clients and collect soft (unverifiable) information to support their lending decisions (Petersen 2004). Such information is subjective in nature and may contain, for example, assessments of the client's character or reliability (Berger and Udell 2004). It is difficult to communicate and share this information within the bank and bankers may distort this information to increase deal flow (Berg 2015). The origination of large, syndicated loans is particularly dependent on bankers developing close relationships with their clients (Engelberg, Gao, and Parsons 2012; Herpfer 2018). Soft information thus plays an indispensable role in the corporate lending market. One can reasonably assume that banks face information asymmetry in assessing bankers' types.

Second, we argue that bankers face a competing incentive to generate new deals. According to the Bureau of Labor Statistics, bankers are often compensated based on loan volume. Moreover, corporate bankers are encouraged to prospect clients and cross-sell other banking products. These competitive pressures can create a short-run incentive for bankers to focus on

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[7] Granted, credit events can also arise if bankers experience bad luck. As long as bankers' abilities or efforts can still influence the occurrence of a credit event, the event should still be an informative signal.

[8] Bankers may directly influence risk management through their influence on loan covenants. In addition, bankers may indirectly influence risk managers by manipulating or obfuscating information that is important for the loan approval process (see, e.g., Berg 2015; Berg, Puri, and Rocholl 2016).

originating new loans without imposing high screening standards. The dual focus on volume and loan quality may also lead a banker to reduce monitoring efforts, as loan volume is a more quantifiable and rewarded performance metric (Holmström and Milgrom 1991).

Third, credit events are costly for banks. The average loan in our sample has a face value of approximately $400 million, and prior studies indicate that many banks retain a large portion of the loans they originate and that risky loan sales in the secondary market are subject to large discounts (Wittenberg-Moerman 2008; Benmelech, Dlugosz, and Ivashina 2012; Irani and Meisenzahl 2017). This suggests that credit events can generate significant capital losses and that the risk associated with structuring failed loans is not costlessly passed on to other investors. Credit events are also costly because they impair a bank's reputation with its syndicate partners and compromise its ability to structure future deals (Gopalan, Nanda, and Yerramilli 2011).

Based on these assumptions, we expect banks to impose disciplinary actions upon observing credit events. This conjecture is also supported by evidence from practice suggesting that disciplining is an integral part of a bank's risk management strategy. Major consulting firms, including Deloitte and Ernst and Young, advise banks to enforce disciplining to build a healthy risk culture among their employees. Their suggested practices include a "carrot and stick" approach (Hida and Leake 2015) and enforcing "strong consequences for misbehavior through performance management, compensation, and disciplinary actions" (Ernst and Young 2014). Many banks follow such principles and formally implement disciplining practices in written risk management policies. For example, UBS looks for any "small signals or patterns across a variety of indicators" as early warning signs and then uses such signals as a "mechanism for performance evaluations or decisions on disciplinary action" (UBS 2016).

Termination, in particular, can be an effective disciplining tool due to the career-related costs it generates. Prior studies indicate that turnover is costly for workers due to the loss of firm-specific human capital and information frictions associated with finding a new job (Greenwald 1986; Jacobson, LaLonde, and Sullivan 1993; Şahin et al. 2014). Turnover in the corporate banking sector may be particularly costly because bankers' value is derived, in part, from the business relationships they have developed with their clients over time, and there may be frictions in transitioning these relationships to a new bank. For example, clients may be unwilling to follow the banker to a new bank if they have developed strong ties with the current bank across other product lines or if legal frictions, such as noncompete or nonsolicitation agreements, prohibit bankers from moving their business relationships (Clifford and Gerken 2017). Consistent with this argument, recent research by Herpfer (2018) suggests that bankers often lose clients after departing a bank.

Empirically, we test whether banks terminate bankers following credit events by examining the extent to which banker turnover increases in the year immediately following the occurrence of a ratings downgrade, default, or bankruptcy in a banker's portfolio. We summarize our primary empirical prediction as follows:

Empirical Prediction: *Bankers are more likely to depart the bank in the period immediately following a credit event (i.e., ratings downgrade, default, or bankruptcy).*

We note that our prediction is not without tension. As we discuss in the theoretical framework (Section IA.1), banks may not respond to credit events if the revealed behavior is consistent with their risk-taking preferences. For example, bank managers (and shareholders) may tolerate credit events if they are focused on generating short-term profits, which may involve issuing low quality loans to their clients and cross-selling other products. In addition, our framework suggests that banks may not respond if they are unable to determine whether the credit event arises due to "bad luck." Ultimately, observing an association between credit events and turnover depends on whether the event helps to reveal bankers' types and whether the event indicates risk-taking behavior that is incongruent with banks' preferences.

2. Data and Empirical Methodology

2.1 Data sources and sample construction

We construct our sample by combining data from four primary sources. First, we collect information from LPC DealScan for all privately placed debt contracts issued to public firms between 1994 and 2012. We restrict our sample to loans with available information on contract terms (e.g., spreads, maturity). Next, we match borrowers to Compustat and retain only loans issued to firms with requisite financial information. We exclude firms in the financial and utility industries. Using this matched sample of borrowers and loan contract terms, we next collect information regarding bankers' identities from SEC filings. This results in an initial sample containing 4,215 loans.

For our turnover analyses, we collect detailed information regarding bankers' employment histories from LinkedIn. Doing so allows us to precisely trace the career transition dates for each banker identified in the SEC data set. We discuss the SEC and LinkedIn data in more detail below.[9] Matching with LinkedIn data yields a sample of 2,399 syndicated loan agreements jointly extended by 1,416 unique bankers from 101 unique banks. For each banker, we extend his or her employment path over time, thus constructing a banker-bank-year panel. For each observation, we construct an outstanding loan portfolio based on all the loans issued by the banker from his or her bank of employment

[9] We obtain LinkedIn profiles for 34% of bankers. Our sample size is limited, because we only use public profiles and exclude common names with duplicate matches. We conduct additional analyses in Section 5.5 to alleviate concerns related to limited LinkedIn data.

between the years of loan issuance and loan maturity. If a borrower files for bankruptcy or defaults prior to loan maturity, we remove that loan from the banker's portfolio the year after the event. We further remove all observations for which a banker has no outstanding loans. This results in a final sample containing 7,585 banker-bank-year observations.

2.2 SEC filings

We extract bankers' identities following the procedure outlined in Bushman et al. (2019). 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-Ks, 10-Qs and 10-Ks. In particular, we search for any public filing containing an appended Exhibit 10 (which relates to "Material Contracts").

Next, we require the contract to contain either the word "loan" or the word "credit," followed by the word "agreement" in the title, to ensure that the contract relates to a loan agreement, as opposed to another material agreement (e.g., supply agreements, executive compensation agreements). We search all filings meeting this criterion in the 90-day window centered on the loan date observed in DealScan. Doing so allows us to account for errors in the reported DealScan dates (Murfin 2012). We then match each contract to the corresponding DealScan loan using the names of all banks in the syndicate.

To identify bankers responsible for issuing each loan contract, we examine the signature pages commonly attached to the end of loan agreements. Most of these contracts are electronically filed, so 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 the name of the banker, the bank in which he or she is employed, and the job title. We then match each banker's identity to the respective DealScan loan.

2.3 LinkedIn career data

As we are interested in examining how credit events relate to bankers' career outcomes, we must further identify bankers' career trajectories. A limitation of the SEC data set is that it only indicates a banker's employer at the time of loan issuance but does not capture the exact start date and end date of the banker's employment, the dates associated with a banker's promotions or demotions within a bank, or an individual's transitions between banks. Accordingly, we augment the SEC data with additional data from LinkedIn public profiles. These data provide us with detailed information on the bankers' professional backgrounds and career paths. We match each banker observed in an SEC credit agreement to his or her respective online profile based on the banker's first and last name, name of current employer, and date of employment.[10] Using LinkedIn profiles, we determine the first year and the last year of a banker's employment at a given bank and span the banker's employment across all of the years in between transition dates. These data indicate that 450 exits are related to the 1,416 bankers in our sample (discussed in more detail below).

2.4 Primary empirical methodology

We test the relationship between banker turnover and credit events using the following empirical model:

$$Exit_{\mathrm{ibt}} = \beta Credit\ Event_{\mathrm{ibt}} + \theta Controls_{\mathrm{ibt}} + \gamma_{jt} + \psi_b + \eta_i + \varepsilon_{\mathrm{ibt}}, \tag{1}$$

where i represents a banker, b represents a bank, j represents the primary industry of banker i, and t indicates the year of observation.[11] The outcome variable *Exit* is a binary variable indicating that banker i exits bank b during year t. We set $Exit_{ibt}$ equal to one if year t is the last year that banker i is employed at bank b, and zero otherwise.

Our main variable of interest in this model is *Credit event*, a binary variable equal to one if a credit event (defined below) occurs in year t or t-1 within the loan portfolio of banker i,and zero otherwise. A positive loading on this variable provides evidence that turnover increases following credit events. We allow bankers a 1-year window to exit from their current employment and only consider credit events occurring in the same year or the previous year of the year of departure.[12] If banks terminate bankers after credit events, we expect β to be positive.

Equation (1) also includes a wide set of fixed effects and control variables to better isolate the relationship between loan performance and turnover. We control for bank fixed effects (ψ_b) to remove any time-invariant tendencies that banks may have to turn over their employees. We further control for banker fixed effects (η_i) to remove time-invariant characteristics of the banker, such as risk appetite, personality, and education. Finally, we include borrower industry-year fixed effects (γ_{jt}) of the primary industry that a banker lends to. This helps control for time-varying industry conditions that are relevant for bankers' career opportunities if they specialize by industry groups. The model also includes a vector of controls relating to loan portfolio characteristics that can affect loan performance ($Controls_{ibt}$). Specifically, we control for the average level

[10] We define a lender based on the ultimate bank holding company level as of 2016. This definition removes the possibility of overidentifying banker exits due to bank mergers or intrabank transfers between different divisions. Online profiles also contain a more precise identification of parent banks compared with subsidiaries.

[11] We define a banker's primary industry as the 1-digit SIC industry in which the banker has issued the highest number of loans.

[12] Our results are robust to alternative windows, such as only year $t$or t-1, or 3 years prior to the year of departure, that is, year t-2, year t-1, and year t. In the Internet Appendix (Section IA.8), we show that our results are robust when defining credit events based on only year t-1 and when controlling for additional lags.

of loan spreads (*Loan spread*), log loan amounts (*Loan size*), maturity (*Loan maturity*), and time since origination (*Time since origination*) across a banker's outstanding loan portfolio. In addition, to account for the possibility that bankers with larger portfolios may be more likely to experience credit events, we control for the total number of outstanding loans in the banker's portfolio at each point in time (*Portfolio size*). These controls help to isolate the extent to which realized credit risk is associated with heightened turnover rates. In additional analyses, we also construct an abnormal credit event measure that accounts for borrowers' observable information at origination and augment this model with alternative measures of credit risk. We will discuss these approaches in more detail in Sections 4.2 and 4.3. The appendix defines the variable in detail.

We consider two types of credit events with varying levels of severity. The first type of credit event entails a borrower receiving a ratings downgrade, as this likely indicates deterioration in a borrower's credit quality. We construct an indicator variable, *Downgrades*, that equals one if at least one borrower in a banker's portfolio receives a downgrade from S&P in a given year, and zero otherwise. While ratings downgrades may not present an imminent threat to banks' capital, they can generate reputation damage and may attract bank managers' attention (Gopalan, Nanda, and Yerramilli 2011).

In the second category, we examine more severe credit events, which include defaults and corporate bankruptcies. We gather data on defaults using S&P default rating categories ("D" or "SD") and collect bankruptcy data from the UCLA LoPucki Bankruptcy Research 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 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. We aggregate both types of credit events and create an aggregate measure reflecting poor loan performance, *Credit event*. This measure equals one if a banker experiences at least one downgrade, default, or bankruptcy in his or her portfolio, and zero otherwise.

3. Descriptive Analyses

Table 1 summarizes banker exits and credit events in our sample. The average likelihood that a banker in our sample will exit a bank is 6%, a value indicating that exits are not very common. There is a 10% chance that a banker experiences a credit event in a given year, suggesting that credit events are also relatively uncommon. Across the two types of credit events, we find that downgrades are more common, with a 9% chance of occurring. In contrast, defaults are rare events, with an only 2% likelihood of occurring within the past 2 years.[13]

[13] Downgrades and defaults can occur simultaneously, so the two credit event types overlap some.

Table 1
Summary statistics

Variable	N	Mean	Median	SD
Exit	7,585	0.06	0	0.24
Downgrade	7,585	0.09	0	0.29
Default/bankruptcy	7,585	0.02	0	0.13
Credit event	7,585	0.10	0	0.30
Covenants	7,585	2.00	2	1.11
Strictness	6,865	0.43	0.4	0.33
Loan spread	7,585	164.80	150	105.23
Loan size	7,585	19.61	19.65	1.01
Loan maturity	7,585	3.83	3.98	0.44
Time since origination	7,585	2.11	1.93	1.80
Portfolio size	7,585	3.78	2	5.67

This table displays the summary statistics for variables used in the main analyses. The turnover sample contains 7,585 banker-bank-year observations.

Table 2
Bankers' roles and skills

A. Job titles

Rank	**Job title**	**Percent**
1	Assistant vice president	0.4
2	Vice president	18.2
3	Senior vice president	20.2
4	Director	12.0
5	Managing director	18.1
n/a	Other/unreported	31.2

B. Top-ten skills

#	**Skill**	**Frequency**	**# of profiles**	**% of profiles**
1	Banking	324	304	67.6
2	Portfolio management	307	293	65.1
3	Credit	296	278	61.8
4	Credit analysis	278	261	58.0
5	Financial analysis	255	243	54.0
6	Loans	252	234	52.0
7	Commercial banking	242	227	50.4
8	Capital markets	227	213	47.3
9	Finance	204	196	43.6
10	Corporate finance	202	192	42.7

The table outlines bankers' roles and skills. Panel A presents a standardized ranking of roles in the corporate banking industry, as indicated on Wall Street Oasis Investment Banking Industry Reports (https://www.wallstreetoasis.com/investment-banking-industry-reports). Panel B presents a frequency table of skills disclosed in bankers' online LinkedIn profiles.

In terms of the control variables used in our analyses, the average banker has approximately four loans outstanding per year and the average portfolio contains loans priced at approximately 165 basis points above LIBOR, with average maturity of nearly 4 years. Our sample loans are also very large, with an average face value of $328 million (i.e., exp(19.61)).

Table 2 provides more details about the bankers in our sample. In panel A, we tabulate bankers' roles (when data are available). A large portion of bankers (38.8%) are vice presidents (i.e., assistant vice president, vice president, or senior vice president). Directors and managing directors account for 12.0% and 18.1% of the banker population, respectively. In panel B, we present the top-ten skills most frequently listed by bankers on their LinkedIn profiles. The column "Frequency" indicates the number of times a term is used, whereas "# of profiles" and "% of profiles" represent the number and percentage of profiles containing at least one instance of a term, respectively. The terms listed here appear to be indicative of corporate banking activities. For example, 67.6% of profiles mention "Banking," and 61.8% indicate "Credit." The vast majority of profiles (80.6%) include at least one instance of the terms "Credit," "Credit Analysis," and "Commercial Banking." Overall, this analysis helps confirm the accuracy of our LinkedIn matches.

As we rely on information from LinkedIn in our turnover analyses, our sample naturally consists of only bankers that utilize this platform. As LinkedIn gained popularity in the mid-2000s, we expect to observe more bankers in recent years. We also expect our sample to contain younger bankers as these individuals are more likely to maintain an online presence. Figure 1 describes the composition of our sample of bankers over time, including their age. Panel A reports the distribution of bankers by the year of observation, and panel B represents the distribution of banker observations by age, calculated based on the year in which they graduated college. Consistent with our conjecture, the patterns suggest that we observe more bankers in the 2000s than in the 1990s. Moreover, the majority of bankers in our sample are between the ages of 30 and 40.

Departure rates may vary systematically across banks and over time. Next, we examine univariate trends in departure rates for the most prominent banks in our sample and across all banks over time. Panel A of Figure 2 presents departure rates by bank. The horizontal axis shows the top-ten banks, based on declining loan volumes (from left to right). The columns show the average number of bankers observed within a bank per year in our sample (left vertical axis). The red line represents the likelihood of a banker exiting in a given year (right vertical axis). The figure shows that banks that are known to have higher deal volume, such as Bank of America and JP Morgan, employ the largest number of bankers. Turnover rates also exhibit heterogeneity across large banks.

Panel B of Figure 2 displays bankers' exit patterns by year. The columns show the number of bankers identified each year, and the solid line represents the proportion of bankers departing their current bank relative to the total number of bankers employed that year. The horizontal axis shows years. Admittedly, our sample is smaller in earlier years because of limited coverage from both the SEC and LinkedIn (as discussed above). In recent years, however, the number of bankers has held relatively stable at a range of 800 to 1,100. Exit ratios appear to peak in 2000 and 2012, and we also find a small increase in exit rates around the 2008 financial crisis. We note that inferences from our analyses remain unchanged when we restrict the sample to more recent years (i.e., 2006–2012).

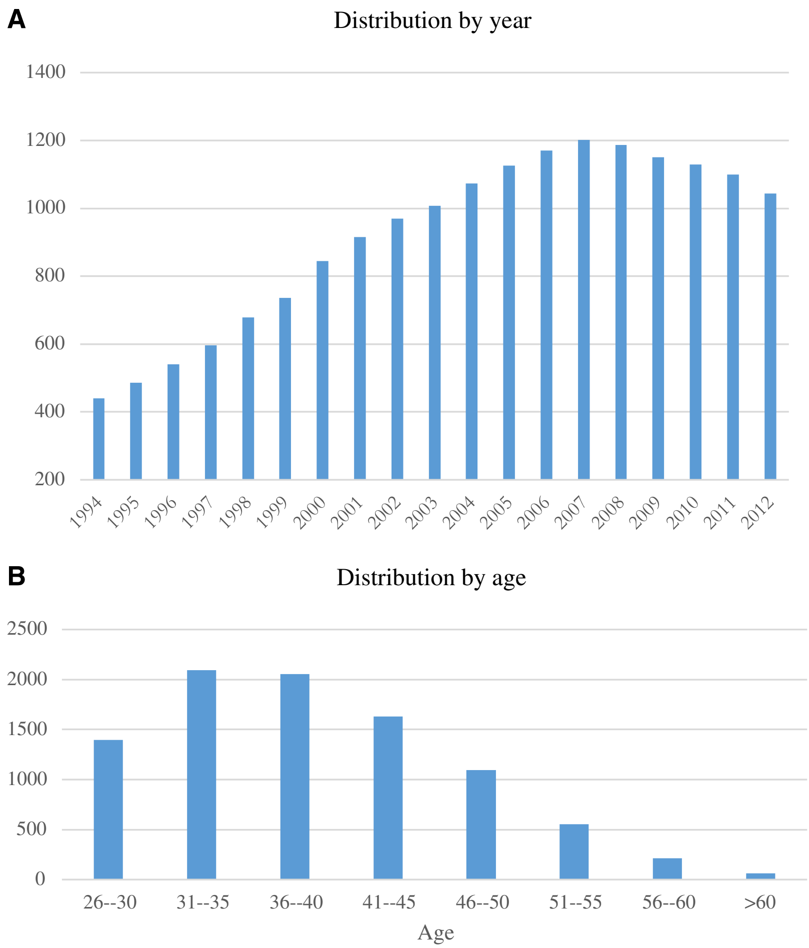

Figure 1
Composition of sample bankers
This figure presents the distribution of bankers identified on LinkedIn. Panel A reports the number of bankers identified each year. The horizontal axis indicates years, and the vertical axis indicates the number of bankers. Panel B reports the number of banker-year observations based on age range. The horizontal axis indicates banker age, and the vertical axis indicates the number of observations.

4. Main Results

4.1 Credit events and banker exit

Our first analysis examines the relationship between credit events and banker exits. Table 3 presents results from estimates of Equation (1). In Column 1, we first consider the univariate relationship between credit events and banker turnover. We then augment the model with controls for loan portfolio characteristics in Column 2, bank- and industry-year fixed effects in Column 3, and banker fixed effects in Column 4.

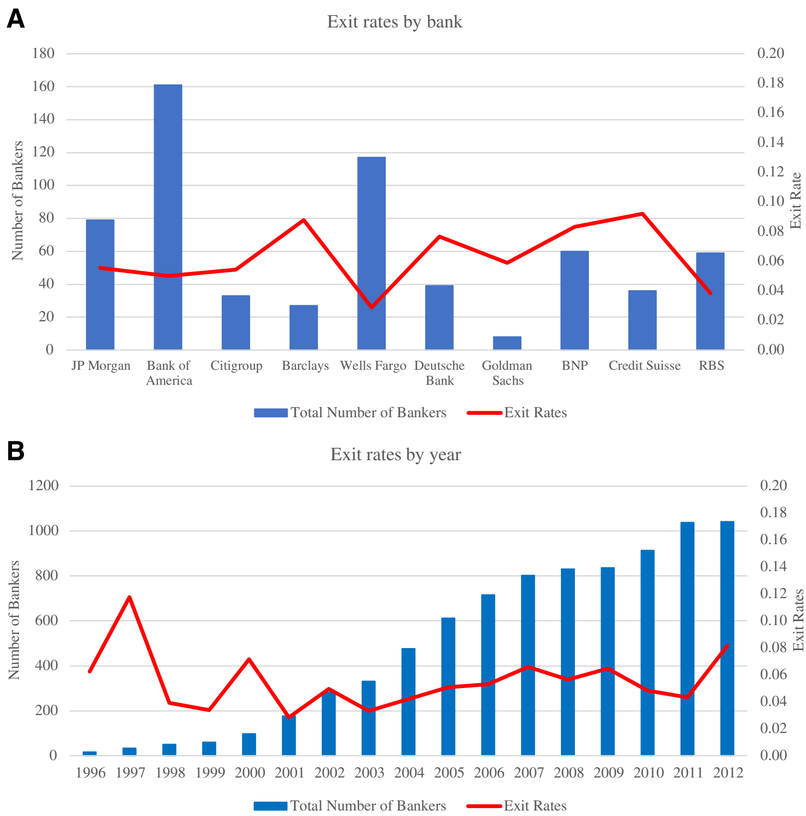

Figure 2
Exit patterns of bankers
This figure presents patterns of banker departure by bank and year. Panel A reports departures by bank. The columns represent the number of bankers in each major bank, and the solid line represents the proportion of bankers that depart that bank in a given year. Panel B reports departure patterns by year. The columns represent the number of bankers identified each year, and the solid line represents the proportion of bankers that exit each year. In both panels, the left vertical axis shows the number of bankers, and the right vertical axis shows departure rates.

The results from this initial analysis suggest a positive and significant relationship between credit events and banker turnover. The results indicate that a credit event is associated with a 3.2 percentage point increased likelihood of departure in the univariate test (Column 1). The coefficient remains relatively stable when we include portfolio characteristics in Column 2, and continues to indicate a 3.2 percentage point increased likelihood of departure. The inclusion of bank- and industry-year fixed effects in Column 3 also produces similar inferences. In our most stringent specification, we add banker fixed effects in Column 4. The results indicate that exit rates increase by 2.9 percentage points following a credit event. This increase is economically meaningful given the sample average exit rate of 6.0 percentage points and suggests that

Table 3
Credit events and banker turnover

Dep. var.: *Exit*	(1)	(2)	(3)	(4)
Credit event	0.0320***	0.0323***	0.0278***	0.0290**
	(3.15)	(3.17)	(2.72)	(2.57)
Loan spread		0.0000	−0.0000	0.0000
		(0.85)	(−0.51)	(0.25)
Loan size		0.0029	−0.0012	0.0031
		(0.93)	(−0.33)	(0.43)
Loan maturity		0.0082	0.0036	−0.0088
		(1.43)	(0.55)	(−0.67)
Time since origination		0.0035**	0.0030*	0.0122***
		(2.41)	(1.74)	(4.06)
Portfolio size		−0.0006**	−0.0013***	−0.0002
		(−2.20)	(−2.93)	(−0.28)
Industry-year FE	No	No	Yes	Yes
Bank FE	No	No	Yes	Yes
Banker FE	No	No	No	Yes
Observations	7,585	7,585	7,585	7,585
Adj. R-squared	.0015	.0022	.0140	.1930

This table examines the relation between credit events and banker turnover. The dependent variable is *Exit*, an indicator variable that equals one if a banker exits a bank in a given year, and zero otherwise. The independent variable of interest is *Credit event*, an indicator variable that equals one if a firm in a banker's portfolio experiences a rating downgrade, default, or bankruptcy in the current or previous year, and zero otherwise. The appendix defines the variables in detail. Standard errors are clustered by bank-year, and t-statistics are presented in parentheses. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

bankers experiencing a credit event face an approximately 50% increase in the relative likelihood of departure. These initial analyses are consistent with our empirical prediction and suggest that banks impose disciplining consequences on employees who generate credit risk exposure.

4.2 Abnormal credit events and banker exit

Next, we consider an alternative measure of credit events that explicitly accounts for observable, hard information that might predict credit events. Doing so allows us to focus more on the risk exposure that is not evident to banks at loan origination and for which bankers are likely held more accountable (i.e., soft information used in screening and monitoring borrowers). In this framework, we assume that loan failures can be attributable to poor borrower fundamentals at loan issuance or to bankers exerting insufficient efforts in screening the borrower and monitoring the borrower's performance after loan issuance. We expect bankers to be held less accountable for loan failures that arise due to poor borrower fundamentals, as such information was available and observable to the bank prior to deal origination and used in its internal credit-scoring model. In contrast, bankers are more likely to be held accountable when borrowers that look highly qualified "on paper" experience credit events. In such instances, a banker's soft information about the borrower can be more useful in preventing and mitigating loan failure. To isolate the extent to which bankers should be held accountable for a credit event, we first estimate the following portfolio-level regression:

$$Credit\ event_{\mathrm{ibt}} = \lambda Firm\ char_{\mathrm{ibt}} + \gamma_{jt} + \varepsilon_{\mathrm{ibt}}, \tag{2}$$

Table 4
Abnormal credit events and banker turnover

Dep. var.: *Exit*	(1)	(2)	(3)	(4)
Abnormal credit event	0.0294***	0.0294***	0.0270**	0.0288**
	(2.59)	(2.59)	(2.41)	(2.46)
Controls	No	Yes	Yes	Yes
Industry-year FE	No	No	Yes	Yes
Bank FE	No	No	Yes	Yes
Banker FE	No	No	No	Yes
Observations	6,908	6,908	6,908	6,908
Adj. R-squared	.0012	.0017	.0120	.2025

This table examines the relation between abnormal credit events and banker turnover. The dependent variable is *Exit*, an indicator variable that equals one if a banker exits a bank in a given year, and zero otherwise. The independent variable of interest is a measure of *Abnormal credit event*, which is calculated as the residuals from regressions of credit events on portfolio average of firm characteristics at origination (Equation (2)). The appendix defines the variables in detail. Standard errors are measured using a bootstrap technique that iteratively resamples the data set 500 times with replacement, and t-statistics are presented in parentheses. *$p<.1$; **$p<.05$; ***$p<.01$.

where the vector *Firm char* includes the following borrower characteristics: size, capital expenditures, market-to-book, cash holdings, profitability, tangibility, cash flow, and a rated dummy. All firm characteristics are measured at the year prior to loan origination and carried throughout the span of the loan. For each year of observation, we take the average values of borrower fundamentals across all outstanding loans in a banker's portfolio. Industry-year fixed effects are denoted by γ_{jt}. We define *Abnormal credit event* as the residuals ($\varepsilon_{\mathrm{ibt}}$) extracted from the above regression. The predicted component of credit events in Equation (2) thus relates to observable borrower fundamentals and reflects the extent to which credit events arise due to weak borrower fundamentals. Once we remove the predicted component, the residuals are suggestive of bankers' screening and monitoring efforts, with higher values of *Abnormal credit event* corresponding to cases in which healthy borrowers experience a credit event. In such cases, it is more likely that the banker was deficient in screening or monitoring the borrower. We provide the results from estimating Equation (2) in Section IA.11 of the Internet Appendix.

Table 4 provides results from estimates of Equation (1) using the abnormal credit event measure. As this analysis is a two-stage process, we now bootstrap standard errors in the second stage by iteratively resampling the data set 500 times with replacement. Column 1 indicates a positive and significant relationship between abnormal credit events and turnover in the univariate setting. The results persist in Columns 2 through 4 after varying the inclusion of portfolio controls and fixed effects. The economic magnitudes are meaningful and consistent with the univariate result (approximately 2.9 percentage points). The magnitudes from these analyses are also similar to those based on raw credit events (Table 3 and Section 4.1). Overall, the results from the abnormal credit events suggest that turnover increases for bankers who fail to manage credit risk.

4.3 Benchmarks for assessing risk-taking

Next, we consider several prevalent benchmarks that banks can use when assessing bankers' lending standards. Recent research shows that syndicated loans are often priced based on recently closed, comparable deals (Murfin and Pratt 2018). The pricing and performance of these deals provide natural benchmarks for assessing credit risk both at loan origination and upon the occurrence of a credit event. For example, the spreads charged on comparable deals indicate the market's evaluation of a borrower's credit risk and the "appropriate" premium associated with a given risk level. Similarly, the performance of comparable deals serves as a reference point for evaluating loan performance. Controlling for these benchmarks allows us to compare a banker's lending standards to the standards of other bankers issuing loans in the same market segment.

Following this logic, we augment Equation (1) with two sets of control variables that account for comparable loans' riskiness. First, we use the average spreads of comparable deals for a banker's portfolio of loans as an "ex ante" benchmark of credit risk. For each loan in a banker's portfolio, we find comparable deals that are in the same SIC two-digit industry group and issued in the one-year window prior to the issuance of the loan of interest, excluding the loan of interest. Within the same industry-year group, we further classify loans by borrowers' distance-to-default, credit ratings, maturity category, and loan types.[14] We then calculate the average spreads for different combinations of comparable loan groups and use them as measures of benchmark risk.

In addition, we introduce a benchmark spread based on a credit-scoring model that incorporates a more comprehensive set of borrower and loan characteristics. This model utilizes all DealScan loans extended to public firms prior to the year of a loan's issuance and regresses *Spread* on the same set of firm characteristics described in Equation (2) and industry-year fixed effects. Next, we use coefficient estimates from this model to predict a fitted value using characteristics of the loans in our sample. We define the fitted value as the benchmark spread. Through both of the above approaches, controlling for the benchmark spread allows us to interpret the coefficient on *Credit event* as banks' response to risk exposure in excess of the benchmark risk level.

Our second set of risk controls use the occurrence of credit events among comparable loans as an "ex post" benchmark of credit risk. For each group of comparable loans defined above, we construct an indicator variable equal to one if any comparable loan experiences a credit event during the year of observation or the previous year, and zero otherwise. This measure characterizes the riskiness of a loan using the realized riskiness of other loans that are similar

[14] We consider four distance-to-default categories (sample quartiles), four ratings categories (i.e., above A- [inclusive], below A- and above BBB- [inclusive], below BBB- and above B- [inclusive], and below B-), four maturity ranges (12 months or shorter, between 12 and 36 months [inclusive], between 36 and 60 months [inclusive], and above 60 months), and three loan types (term loans, revolvers, and others).

at origination. It can serve as a natural reference point when banks assess bankers' lending standards.

Table 5 provides the results from analyses that control for various benchmarks of risk exposure. In Columns 1 through 4, we measure loan riskiness based on comparable spreads. Column 5 controls for the comparable spread based on the credit-scoring model. In Columns 6 through 9, we measure loan riskiness based on comparable credit events. We consider four definitions of comparable loans. Columns 1 and 6 define comparable loans as loans issued to firms in the same industry during the same year, and belonging to the same ratings category. Columns 2 and 7 classify comparable groups using industry-year and distance-to-default categories. Columns 3 and 8 use loans issued to borrowers in the same industry-year, ratings category, and maturity range. Finally, in our most stringent specification, Columns 4 and 9 use industry-year, ratings category, maturity group, and loan type to classify comparable loans. In other words, Column 4 controls for the average spreads charged on loans that are the same type (e.g., revolver, term loan) with the same maturity range and issued to borrowers operating in the same industry group, during the same year, with the same credit rating category. Across all specifications, *Credit event* continues to generate a positive and significant coefficient, suggesting that bankers face heightened turnover likelihood when they generate higher credit risk exposures relative to prevalent measures of credit risk in the market.[15]

4.4 Cross-sectional tests

The results thus far indicate that credit events are associated with increased banker turnover, suggesting that banks impose disciplining consequences on risk-taking. In Table 6, we conduct two sets of cross-sectional analyses to help strengthen our inferences. We first examine the degree to which bank-level punishment varies based on the severity of the event. If banks are concerned about loan failures, we expect turnover to be more pronounced for more severe credit events. Second, we examine whether a banker's turnover likelihood following a credit event is moderated by the banker's lending standards. If our results are consistent with banks managing employee risk-taking, we expect that bankers who generally issue loans with more lenient risk management terms to face greater turnover rates.[16]

[15] In Section IA.12 of the Internet Appendix, we also examine a model that includes *Credit event, Comparable loan event*, and the interaction of the two. Our results continue to indicate that credit events increase turnover. We also find that the interaction term is negative, although not significant, suggesting that the effect of credit event on turnover diminishes when comparable loans also default.

[16] In the Internet Appendix (Section IA.3), we examine how turnover rates vary by banker seniority. We find that the turnover effect is concentrated among junior bankers and no evidence of turnover following credit events arising in senior bankers' portfolios. These findings are consistent with predictions of the career concerns framework (e.g., Chevalier and Ellison 1999).

Table 5
Benchmarks for risk-taking

Dep. var.: *Exit*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Credit event	0.0272**	0.0300***	0.0297**	0.0301**	0.0245**	0.0273**	0.0293**	0.0293**	0.0300**
	(2.36)	(2.63)	(2.54)	(2.53)	(2.14)	(2.37)	(2.58)	(2.49)	(2.50)
Comparable loan spread	−0.0000	−0.0001*	0.0000	0.0001	0.0002				
	(−0.00)	(−1.75)	(0.08)	(0.93)	(1.62)				
Comparable loan event						0.0212	0.0388	0.0123	−0.0001
						(1.27)	(1.38)	(0.77)	(−0.00)
Comparable group	industry, rating	industry, distance-to-default	industry, rating, maturity	industry, rating, maturity, loan type	credit scoring model using all DealScan	industry, rating	industry, distance-to-default	industry, rating, maturity	industry, rating, maturity, loan type
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banker FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,419	7,386	7,178	7,052	6,932	7,420	7,386	7,178	7,052
Adj. R-squared	.1989	.2026	.2008	.1985	.2022	.1990	.2025	.2007	.1984

This table examines the relation between credit events and banker turnover after controlling for benchmarks of credit risk. The dependent variable is *Exit*, an indicator variable that equals one if a banker exits a bank in a given year, and zero otherwise. The independent variable is *Credit event*, an indicator variable that equals one if a firm in a banker's portfolio experiences a rating downgrade, default, or bankruptcy in the current or previous year, and zero otherwise. Columns 1 through 4 control for benchmark spreads, based on comparable borrower groups defined by criteria indicated in the row titled "Comparable group." Column 5 controls for comparable spreads based on a credit scoring model using all DealScan loans extended to public firms prior to the year of a loan's issuance. Columns 5 through 9 control for benchmark default events based on comparable borrower groups. The appendix defines the variables in detail. Standard errors are clustered by bank-year, and t-statistics are presented in parentheses. *$p<.1$; **$p<.05$; ***$p<.01$.

Table 6
Cross-sectional analyses of banker turnover

A. Credit event types

Credit event partition	*Type*		*Bankers' role*		*Allocation*	
Dep. var.: *Exit*	(1) Default	(2) Downgrade	(3) Lead	(4) Participant	(5) High	(6) Low
Credit event	0.0620**	0.0265**	0.0576***	−0.0020	0.0414***	−0.0140
	(2.24)	(2.45)	(3.20)	(−0.08)	(3.40)	(−0.64)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Banker FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,585	7,585	7,585	7,585	7,585	7,585
Adj. R-squared	.1928	.1928	.1938	.1919	.1936	.1919

B. Banker lending standards

Risk-adjusted terms	*Covenants*		*Strictness*	
Dep. var.: *Exit*	(1) Low	(2) High	(3) Low	(4) High
Credit event	0.0416**	0.0081	0.0482**	0.0038
	(2.29)	(0.49)	(2.56)	(0.24)
Controls	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Banker FE	Yes	Yes	Yes	Yes
Observations	3,404	3,197	3,119	2,926
Adj. R-squared	.2304	.2081	.2016	.2335

This table examines how the relation between credit events and banker turnover varies based on the severity of the credit event and a banker's risk management effort. The dependent variable is *Exit*, an indicator variable that equals one if a banker exits a bank in a given year, and zero otherwise. Panel A considers variation in credit event type. Columns 1 and 2 redefine *Credit event* based on whether the event is related to a downgrade (Column 1) or default (Column 2). Columns 3 and 4 redefine *Credit event* based on banker's role in the syndicate. In Column 3, credit events include only those occurring to loans underwritten by lead bankers, and in Column 4, credit events include only those occurring to loans underwritten by participants. Columns 5 and 6 redefine *Credit event* based on allocation. In Column 5, credit events include those occurring to lead banks with over 5% share, and in Column 6, credit events include those occurring to participant banks or banks taking less than a 5% share. Panel B considers variation in risk-adjusted covenants. Columns 1 and 2 partition the sample based on the number of covenants, and Columns 3 and 4 partition the sample based on the strictness of covenants included in a banker's portfolio. All contract terms are residuals from regressions of the corresponding contract terms on borrower characteristics, loan terms, and industry fixed effects. Each partition is at the bank-year-specific median. The appendix defines the variables in detail. Standard errors are clustered by bank-year, and t-statistics are presented in parentheses. *$p<.1$; **$p<.05$; ***$p<.01$.

4.4.1 Credit event types. Panel A of Table 6 presents the results from our first set of cross-sectional analyses, which varies the severity of the credit event. We partition credit events based on the event type (i.e., ratings downgrade versus default or bankruptcy), the banker's role in the syndicate (lead versus participant), and the bank's allocation in the loan (also known as "skin in the game"). Columns 1 and 2 separate credit events by event type and present the results for *Default* and *Downgrades*, respectively. Ratings downgrades are less severe credit events as they may not present an imminent threat to banks' capital. Our results suggest that defaults increase banker exit by 6.2 percentage points, an effect that is stronger than that generated by downgrades (2.7 percentage points). This difference is near the 10% statistical significance level (p-value = .11).

Next, we consider the banker's role in the syndicate. We expect lead arrangers to be held more accountable for loan failures as they play a greater role in syndicated lending decisions than do participant lenders (Sufi 2007). We separate a banker's credit events into cases where the banker is a lead arranger of the troubled loan and cases where the banker is not. Columns 3 and 4 present the results for these event types separately. We find that lead arrangers face a 5.8 percentage point increase in turnover rates following credit events while participant bankers do not experience any change in the likelihood of departure. The difference in coefficients is statistically significant (p-value $<$ .05) and economically strong.

In our last partition, we consider the share of the loan that a bank contributes to the syndicate. Many loans in the syndicated lending market are dispersedly held, and we expect banks to respond more strongly to credit events when they retain a significant portion of the loan, that is, when they have substantial "skin in the game." We define a high allocation event as one in which a lead bank retains a share of the loan greater than the sample median of 5% (Column 5) and a low allocation event as one in which the bank is a participant or retains less than or equal to 5% of the loan (Column 6). The results suggest that high allocation events lead to a 4.1 percentage point increase in banker turnover rates, while low allocation events do not generate a significant effect on banker turnover. The difference between coefficients is statistically significant (p-value $<$ .10). Overall, the results demonstrate that the sensitivity of a banker's departure rate to credit events varies with the severity of credit events.

4.4.2 Bankers' lending standards. Our second set of cross-sectional analyses examines whether banker turnover varies based on their use of covenants. Covenants represent an important risk management tool in the syndicated loan market, and we expect bankers' usage of covenants to affect how banks impose disciplining consequences for at least two reasons. First, we expect that looser covenants might translate into higher loan losses for the bank. This is because covenants protect creditor rights and provide an opportunity for the bank to renegotiate or secure collateral from the firm both inside and outside default status (Chava and Roberts 2008; Roberts and Sufi 2009; Whitehead 2008; Roberts 2014). Thus, consistent with our results on loan loss severity (Section 4.4.1), the bank will be more likely to respond with disciplining consequences when bankers use less restrictive covenants. Second, a banker's use of ex ante covenant terms may also reflect his or her monitoring efforts. With the inclusion of covenants, the banker will need to frequently check in with the borrower, monitor its activities, and renegotiate if necessary. When a borrower defaults on a loan with numerous restrictive covenants, the bank may infer that the banker exerted substantial levels of effort to mitigate the risk of default or the loss given default. The bank should thus be less likely to hold the banker accountable for such credit events.

To test the moderating effects of covenant usage on bank disciplining, we calculate risk-adjusted lending terms for covenants and covenant strictness in a banker's portfolio. We first define *Covenants* as the number of covenants on a loan and *Strictness* as the probability of a covenant violation following Murfin (2012). We take all of the contract terms of a loan and borrower fundamentals known at the time of origination and expand them to the entire maturity span of the loan. At each point in time, we calculate the average of *Covenants*, *Strictness*, all other contract characteristics (including spread, loan size, and maturity) and the borrower fundamentals specified in Equation (2) across all outstanding loans in a banker's portfolio. We then estimate the following regression model:

$$Lending\ standards_{\mathrm{ibt}} = \lambda_1 Loan\ char_{\mathrm{ibt}} + \lambda_2 Firm\ char_{\mathrm{ibt}} + \kappa_j + \upsilon_{\mathrm{ibt}}, \qquad (3)$$

where *Lending standards* is either *Covenants* or *Strictness*. κ_j is industry fixed effects. We then take the residuals from the above regression, υ_{ibt}, to create risk-adjusted lending term measures. Higher levels of residuals indicate that a loan has abnormally high number of covenants or abnormally tight covenant restrictions.

Panel B of Table 6 reports the results of our cross-sectional analyses based on bankers' lending standards. For each lending term measure, we partition the sample based on the median residuals at the bank-year level so as to distinguish bankers based on how their lending standards differ from the bank's preferences. Columns 1 and 2 partition the sample based on whether a banker imposes below- or above-median number of abnormal loan covenants on their loans, respectively. Columns 3 and 4 partition the sample based on abnormal covenant strictness.[17] Results from these analyses indicate that bankers who issue loans with lax covenant terms are more likely to depart the bank following credit events. In comparison, bankers that issue loans containing a greater number or stricter set of covenants face very low risk of turnover. This is indicated by the statistically insignificant coefficients on the variable *Credit event* in Columns 2 and 4. The differences in coefficients are statistically significant across both subsample partitions (p-value $< .10$). These results indicate that disciplining is concentrated among bankers who fail to protect the bank against credit risk exposure.

Overall, our cross-sectional analyses help strengthen our inferences across several dimensions. First, the results based on event severity demonstrate that credit events are relevant measures of risk exposure. Second, our lending terms analyses confirm that disciplining is related to risk management practices as

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17 We note that our inferences are similar when we compare the exit rates of bankers that have *both* high spreads and high covenants (or strictness) to the exit rates of bankers that have *both* low spreads and low covenants (or strictness). Turnover is more pronounced among low-price and low-covenant (or low-strictness) loans.

bankers issuing loans with lax lending standards face more severe disciplining consequences.

5. Additional Analyses and Robustness

Our results thus far suggest that banks discipline bankers that write risky loans. In this section, we further discuss the implications of these findings and also address alternative explanations for our results. First, we examine the market consequences that bankers face following credit events. Second, we examine whether credit events lead to changes in lending standards, which would be consistent with bankers facing heightened career concerns after credit events. Third, we conduct analyses examining why risk-taking exists in equilibrium, given that bankers appear to face consequences for such behavior. Fourth, we discuss several alternative explanations for our findings. Finally, we examine the robustness of our results to issues related to sourcing our data from SEC and LinkedIn.

5.1 Career outcomes following credit events

Our findings indicate that bankers face increased turnover rates following a credit event. As discussed in Section 1, this discipline is likely costly for bankers, especially in the banking sector due to the potential loss of clients. In this section, we assess whether the external labor market also imposes disciplining consequences on bankers following credit events by examining bankers' career outcomes. In our tests below, we focus exclusively on the 450 exiting bankers and track their next job.

We measure career outcomes after exit using several different methods. We first classify job desirability based on bank size. Bank size represents a reasonable proxy for job quality as larger banks are likely to be more desirable places to work, in part, because they are more prestigious, dominate the client base, and generate higher deal volume (e.g., Hong and Kubik 2003; Ross 2010). We classify downward movements as instances in which a banker moves to a smaller bank, that is, a bank that issued fewer loans in the prior 3 years than the banker's current employer. Similarly, we classify upward movements based on a banker moving to a larger bank.

We note that a potential concern with the above definition of job quality is that bankers may voluntarily choose to move banks for other benefits. Therefore, we consider alternative classifications of career movements based on exits to smaller (larger) banks with lower (higher) quality attributes across other dimensions in addition to size.

To start, we consider the culture and the quality of life of the bank, given that individuals may benefit from moving to banks with better work-life balance, even if the bank is smaller than their previous employer. We collect data on quality of life from Glassdoor.com, a job search and review website. The average (median) bank in our sample has 1,940 (466) reviews, of which 585

(135) provide specific rankings of quality of life. Using these data, we reclassify downward (upward) movements as movements to smaller (larger) institutions that have lower (higher) quality of life (QoL) scores based on these data.

Next, we consider a bank's prestige in the industry, as some smaller, boutique firms are highly regarded by prospective employees due to their expertise in a niche market. Prestige is measured based on rankings provided by Vault, an insider career and job reference tool. We define a banker as moving to a less (more) prestigious institution if the new institution is smaller (larger) and has a lower (higher) Vault ranking than the previous employer.

We also consider the employee's title at the new institution relative to the institution he or she departs from. We codify banker titles (e.g., VPs and directors) using a standardized ranking scheme relevant to the corporate banking sector and classify downward (upward) movements as instances in which a banker takes a strictly lower-ranked (higher-ranked) position at a smaller (larger) institution.[18]

We further explore the possibility that credit events facilitate matching between banks and bankers with similar risk preferences. Recent evidence from Egan, Matvos, and Seru (2019) shows that fraudulent advisors eventually match to firms with similar preferences for misconduct. We proxy for the riskiness of a bank using the bank's overall loan default rates (relative to total outstanding loans) in a given year, and define an downward (upward) move as one in which a banker moves to a smaller (larger) bank with more (less) default events.

Finally, we consider complete exits from the banking industry as one alternative downward career move. If credit events incur large enough reputational damage, bankers may be purged from the banking industry altogether. We code an industry exit as one if a banker moves to an institution not listed in DealScan, and zero otherwise.

We begin by examining the univariate patterns in movement type based on whether a departing banker experiences a credit event. In Table 7, panel A, we examine the six different types of downward movements discussed above. Across all specifications, we find that departing bankers with credit events have a slightly larger tendency to move down than do bankers without credit events, although we note that the differences are not statistically significant. In panel B, we examine the five different types of upward movements. Departing bankers with credit events have a lower tendency to move to better positions than do bankers with no credit events, although the differences are again not significant.

To more formally test whether exits are associated with adverse or better career outcomes, we reestimate Equation (1) using only the sample of departing bankers and replace the dependent variable with *Move down* or *Move up*,

[18] Based on the average salaries reported on Indeed.com, we find that corporate bankers employed by larger banks and bankers with higher ranks generally earn more. For example, managing directors make over $250,000 per year, whereas senior VPs make around $150,000. In large (small) banks, director-level jobs report an annual salary of around $175,000 ($90,000).

Table 7
Credit events and career outcomes

A. Move down by credit event

	Move down type:	*A. Credit event* (%)	*B. No credit event* (%)	Difference (A-B) (%)	t-stat (A - B)	p-value
(1)	Smaller	56.72	53.79	2.93	0.44	.66
(2)	Worse QoL	28.36	23.76	4.60	0.81	.42
(3)	Less prestigious	47.76	44.13	3.64	0.55	.58
(4)	Lower rank	32.84	28.98	3.85	0.64	.52
(5)	Riskier	25.37	21.93	3.44	0.62	.53
(6)	Industry exit	13.43	10.97	2.47	0.59	.56

B. Move up by credit event

	Move up type:	*A. Credit event* (%)	*B. No credit event* (%)	Difference (A-B) (%)	t-stat (A - B)	p-value
(1)	Larger	23.88	32.64	−8.76	−1.43	.15
(2)	Better QoL	16.42	21.15	−4.73	−0.88	.38
(3)	More prestigious	14.93	23.24	−8.31	−1.52	.13
(4)	Higher rank	10.45	12.27	−1.82	−0.42	.67
(5)	Less risky	4.48	9.40	−4.92	−1.32	.19

Table 7
Continued

C. Move down regressions

Dep. var.: *Move down*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Type of movement:	Smaller	Smaller	Worse QoL	Worse QoL	Less prestigious	Less prestigious	Lower rank	Lower rank	Riskier	Riskier	Industry exit	Industry exit
Credit event	0.0222	−0.0309	0.1028	0.0443	0.0554	−0.0259	0.0245	−0.0444	−0.0035	−0.0039	0.0408	0.0376
	(0.32)	(−0.37)	(1.53)	(0.58)	(0.75)	(−0.31)	(0.32)	(−0.56)	(−0.05)	(−0.05)	(0.82)	(0.62)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	450	450	450	450	450	450	450	450	450	450	450	450
Adjusted R-squared	.1713	.2536	.1229	.1282	.0683	.1611	−.0378	.0151	.0305	.0844	.0176	.0608

D. Move up regressions

Dep. var.: *Move up*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Type of movement:	Larger	Larger	Better QoL	Better QoL	More prestigious	More prestigious	Higher Higher rank	Higher rank	Less risky	Less risky
Credit event	−0.0639	−0.0113	−0.0607	−0.0113	−0.1009*	−0.0670	−0.0194	−0.0089	−0.0682*	−0.0451
	(−0.94)	(−0.14)	(−0.97)	(−0.15)	(−1.68)	(−0.93)	(−0.42)	(−0.14)	(−1.90)	(−0.96)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	450	450	450	450	450	450	450	450	450	450
Adjusted R-squared	.1757	.2313	.1535	.1918	.1542	.2643	.0799	.0809	.0757	.1097

This table examines the relation between credit events and career outcomes among the 450 departing bankers in our sample. Panel A present univariate statistics on the percentage of departing bankers experiencing worse career outcomes (i.e., *Move down*) conditional on the banker having a credit event. In row 1, *Move down* is defined by movements to smaller institutions, that is, bankers that issued fewer loans in the prior 3 years. In row 2, *Move down* is defined by movements to smaller institutions with lower quality of life indexes, as per Glassdoor reviews. In row 3, *Move down* is defined by movements to smaller institutions with lower prestige rankings, as per Vault rankings. In row 4, *Move down* is defined as movements to smaller institutions with lower job rankings (see Table 2). In row 5, *Move down* reflects moves to smaller institutions with higher default rates. In row 6, *Move down* is an exit from the banking industry. Panel B presents univariate statistics on the 450 departing bankers experiencing better career outcomes (*Move up*) conditional on the banker having a credit event. In row 1, *Move up* is defined by movements to larger institutions. In row 2, *Move up* is defined by movements to larger institutions with higher quality of life indexes. In row 3, *Move up* is defined by movements to larger institutions with higher prestige rankings. In row 4, *Move up* is defined as movements to larger institutions with higher job rankings. In row 5, *Move up* reflects moves to larger institutions with lower default rates. Panels C and D present multivariate regressions of *Move down* and *Move up* on *Credit event* for the sample of departing bankers using the same movement types as defined above. The appendix defines the variables in detail. In panels C and D, standard errors are clustered by bank-year. t-statistics are presented in parentheses. *$p<.1$; **$p<.05$; ***$p<.01$.

indicator variables that take the value of one if a banker moves to a worse (or better) position, and zero otherwise. In these tests, we continue to focus only on the sample of 450 departing bankers as regressions incorporating the full sample of movers and nonmovers can be contaminated by measurement error. We do not include banker fixed effects in these tests, because most bankers in our sample move only once.

Panel C of Table 7 presents the results of the downward career movement analysis. We test the relationship between credit event and the six different move types, varying the inclusion of industry-year fixed effects. We do not document a significant relationship between credit events and move down across any of the specifications we consider. In panel D of Table 7, we examine a similar set of analyses using *Move up* as our dependent variable. We find some evidence that bankers with credit events are less likely to move to better positions (Columns 5 and 9), but the results are not consistent across all specifications.

Taken together, we do not find that departing bankers consistently move to more or less desirable positions following credit events. This result suggests that bankers experiencing credit events are unlikely to exit to seek better career opportunities in the external labor market. While the univariate statistics indicate that departing bankers have a lower probability of moving up and a higher probability of moving down following credit events, these differences are not statistically significant and do not survive the multivariate regression framework. Collectively, these results generate two important implications. First, exiting bankers do not fare better after credit events, suggesting that credit events potentially impose net costs on the banker, after factoring in the costs of movement and loss of clients discussed in Section 1. Second, we also find no evidence that bankers move down after credit events. One possible explanation for the lack of evidence on downward movements is that new employers cannot fully determine whether the banker was at fault for the credit event. This is consistent with the idea that soft information generated from a loan arrangement is possessed by the lender and not shared by the lending market at large (Berger and Udell 2004; Petersen 2004).

5.2 Do lending standards change following a credit event?

Next, we examine whether credit events prompt changes in lending standards. A banker should face heightened career concerns after experiencing a credit event as the threat of termination and potential reputation damage among syndicate partners increases. These career concerns should motivate the banker to increase monitoring and screening efforts to improve the bank's perception of his or her ability. In this analysis, we focus on lead arrangers as they exhibit the greatest influence on corporate loans and are most responsible for negotiating covenant packages (Sufi 2007; Ivashina 2009). We examine the effects of credit events on future lending standards using the following regression:

$$\begin{aligned} \textit{Lending standard}_k = &\beta_1 \textit{Credit event}_{\text{ibt}} + \beta_2 \textit{Comparable lending standard}_k \\ &+ \beta_3 \textit{Controls}_k + \beta_4 \textit{Portfolio size}_{\text{ibt}} + \gamma_{jt} + \psi_b + \eta_i + \varepsilon_k, \end{aligned} \tag{4}$$

where k represents a loan package, i represents a banker, b represents a bank, and t represents time. The dependent variable, *Lending standard* includes *Covenants* and *Strictness* specified on individual loan contracts issued by banker i. *Credit event* is an indicator for whether there is a credit event arising in banker i's portfolio in the period prior to the origination of loan k. We focus on covenants as prior studies indicate that they are reflective of risk management practices (e.g., Chava and Roberts 2008; Lookman 2009). *Controls* include loan maturity, loan size, loan-type fixed effects, and the average number of covenants and covenant strictness specified on comparable loans. Controlling for comparable lending terms allows us to assess the conservativeness of banker i's lending standards relative to other bankers issuing similar loans.[19] We also include a comprehensive set of fixed effects in this model, including industry-year fixed effects (γ_{jt}), bank fixed effects (ψ_b), and banker fixed effects (η_i). If disciplining leads to stricter lending standards, we should observe $\beta_1 > 0$.

Table 8, panel A, presents the results from this analysis. Columns 1 through 4 show the results for *Covenants* and Columns 5 through 8 present the results for *Strictness*. For each loan term, we first present the results with fixed effects and comparable terms (Columns 1 and 5). We then augment the model with loan-level characteristics (Columns 2 and 6) and spreads (Columns 3 and 7). While comparable lending terms control for the loans extended to borrowers with similar risk profiles, we also control explicitly for a host of borrower characteristics. Specifically, in Columns 4 and 8, we include controls for *Borrower size, Borrower profitability, Borrower tangibility, Borrower M/B, Borrower rated, Borrower cash holdings*, and *Borrower capital expenditures*. The coefficients on *Credit event* are positive and significant in all settings, indicating bankers tighten lending terms following credit events. Overall, the evidence regarding changes in contract terms is consistent with the argument that career concerns motivate bankers to increase their lending standards.[20]

Next, we examine whether the threat of termination at the bank-level motivates bankers to impose stricter lending standards. Granted, termination practices are not explicitly stated in employment contracts and exogenous shocks to such practices are rare. We instead estimate cross-bank differences in the severity of banks' termination policies and assess whether such differences are associated with differences in their bankers' lending standards. For each bank in our sample, we estimate turnover credit event sensitivity, *Bank turnover*

[19] This analysis uses the full sample of SEC loans for which we can identify lead arrangers. We do not require exact career transition dates for this test.

[20] Our inferences are unchanged when we examine only bankers that remain at the bank of interest following the credit event.

Table 8
Credit events and loan terms

A. Banker future lending terms

Dep. var.: *Lending standard* Lending term:	(1) *Covenants*	(2) *Covenants*	(3) *Covenants*	(4) *Covenants*	(5) *Strictness*	(6) *Strictness*	(7) *Strictness*	(8) *Strictness*
Credit event	0.7514**	0.6878**	0.6856**	0.7595**	0.2075***	0.2021***	0.1882***	0.2680**
	(2.28)	(2.17)	(2.17)	(2.37)	(2.87)	(2.94)	(3.12)	(2.51)
Comparable covenants	−0.0091	−0.0103	−0.0101	0.0620	0.1343**	0.1388**	0.1335**	0.1224
	(−0.04)	(−0.05)	(−0.05)	(0.32)	(2.14)	(2.16)	(2.16)	(1.39)
Comparable strictness	0.1790	0.1113	0.1038	−0.0562	−0.0534	−0.0587	−0.0965	−0.3174
	(0.40)	(0.24)	(0.23)	(−0.10)	(−0.45)	(−0.49)	(−0.82)	(−1.25)
Loan maturity		0.1100*	0.1118*	−0.0019		0.0030	0.0110	−0.0046
		(1.85)	(1.92)	(−0.10)		(0.21)	(0.76)	(−0.92)
Loan size		−0.0394	−0.0386	0.0237		−0.0122**	−0.0087	0.0001
		(−1.41)	(−1.44)	(0.86)		(−2.01)	(−1.51)	(0.01)
Portfolio size		−0.0119	−0.0120	0.0000		−0.0091	−0.0090	0.0002**
		(−0.39)	(−0.39)	(0.07)		(−0.86)	(−0.90)	(2.27)
Loan spread			0.0001	0.0819			0.0003***	0.0039
			(0.26)	(1.57)			(3.12)	(0.26)
Loan type FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banker FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. borrower controls	No	No	No	Yes	No	No	No	Yes
Observations	3,092	3,092	3,092	2,708	2,190	2,190	2,190	1,898
Adj. R-squared	.7782	.7795	.7793	.8347	.8503	.8504	.8560	.8775

Table 8
Continued

B. Bank turnover beta and lending terms

Dep. var.: *Lending standard* Lending term:	(1) *Covenants*	(2) *Covenants*	(3) *Covenants*	(4) *Covenants*	(5) *Strictness*	(6) *Strictness*	(7) *Strictness*	(8) *Strictness*
Bank turnover beta	0.4725**	0.7411***	0.6097***	0.6496***	0.4178***	0.5353***	0.3442***	0.3186***
	(2.19)	(3.45)	(2.73)	(2.66)	(5.68)	(6.01)	(4.09)	(3.98)
Comparable covenants	0.5749***	0.0766	0.0728	0.0460	0.0435***	0.0789***	0.0637***	0.0597***
	(14.82)	(1.08)	(0.98)	(0.54)	(3.81)	(3.31)	(2.78)	(2.61)
Comparable strictness	0.4205***	−0.0638	−0.1115	−0.2261	0.4151***	−0.0113	−0.0839	−0.0599
	(3.75)	(−0.36)	(−0.60)	(−1.18)	(11.70)	(−0.17)	(−1.54)	(−0.94)
Loan maturity		0.0076***	0.0076***	0.0077***		0.0013**	0.0015***	0.0012**
		(4.29)	(4.19)	(4.57)		(2.19)	(2.81)	(2.28)
Loan size		−0.0737***	−0.0601**	0.0046		−0.0491***	−0.0331***	−0.0178**
		(−3.03)	(−2.48)	(0.15)		(−6.38)	(−4.44)	(−2.01)
Portfolio size		0.0050	0.0031	0.0086		0.0097***	0.0070***	0.0047**
		(0.61)	(0.40)	(1.10)		(5.02)	(3.58)	(2.47)
Loan spread			0.0006**	0.0007**			0.0008***	0.0007***
			(2.54)	(2.53)			(9.35)	(8.29)
Loan type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Add. borrower controls	No	No	No	Yes	No	No	No	Yes
Observations	2,641	2,388	2,388	2,377	1,823	1,633	1,633	1,624
Adj. R-squared	.1288	.4752	.4771	.4842	.1792	.5287	.5750	.6013

This table examines the relation between credit events and banker's future contracting tendencies. Panel A presents loan-level regressions of *Covenants* and *Strictness* on *Credit event*. Panel B presents loan-level regressions of *Covenants* and *Strictness* on bank-specific measures of turnover sensitivity to credit events (*Bank turnover beta*). In both panels, Columns 1 through 4 present the results for *Covenants*, and Columns 5 through (8) present the results for *Strictness*. The models control for comparable borrower covenants and strictness. The appendix defines the variables in detail. In panel A, Standard errors are double clustered by borrower and banker. In panel B, standard errors are double clustered by borrowers and bankers, and bootstrapped 500 times. t-statistics are presented in parentheses. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

beta, from bank-specific regressions of *Exit* on *Credit event* arising in a lead banker's portfolio. A higher beta implies that a bank exercises a stricter termination policy regarding its employees' risk-taking. The estimated values of beta have a mean of 0.040, a 25th percentile value of -0.006, and a 75th percentile value of 0.047.[21]

Table 8, panel B, presents the results from regressions of lending terms on bank turnover betas. Standard errors are double clustered by borrowers and bankers, and bootstrapped 500 times. The model is identical to Equation (4), except that we exclude bank and banker fixed effects, because this analysis is based on cross-bank variation. We present the results in an order similar to that used in panel A. In all specifications, we find that higher values of bank turnover beta are associated with bankers issuing loans with a greater number of covenants and more restrictive covenants. Although this result does not provide causal evidence between termination policies and employees' risk management efforts, it does suggest a positive association between bank-level disciplining practices and employees' risk management efforts. Our result is thus consistent with predictions from the career concerns framework.

5.3 Why does risk-taking exist in equilibrium?

Given that loan failures are associated with increased rates of turnover, it is natural to question why high levels of risk-taking exists in equilibrium. One explanation is that bankers face competing incentives. While bankers may be encouraged to manage the quality of their loan portfolio, they also have incentives to originate and grow their loan portfolios in order to generate profit, cross-sell products, and remain competitive in the lending market (Acharya and Naqvi 2012).

We conduct additional analyses to validate this explanation. First, to illustrate the presence of conflicting incentives, we collect a large sample of job posting data from Burning Glass Labor Insight, a large database containing the near-universe of job postings. We retain all postings issued for SOC Code 13-2072 ("Loan Officers") with the job title containing the word "corporate" or "syndicate" for the top-twenty largest banks in our sample. Our search returns 667 job postings from 2010 to 2017. Consistent with banks encouraging loan growth, we find that approximately 54% of the postings in our sample emphasize a skill related to loan sales ("Underwriting," "General Lending," or "Sales"). Approximately one-half of the postings strongly emphasize building effective relationships. This suggests that origination and relationship management are important skills in this market. Moreover, the postings also indicate a strong demand for risk management, as 66% of postings explicitly

21 We also examine whether the turnover betas are equal to each other by regressing *Exit* on the interaction of *Credit event* and bank dummies. We then examine whether the coefficients on the interactive terms are statistically different from each other. Our test generates an F-statistic on the interactive terms of 1.44 (p-value =.04), suggesting that the turnover betas of our sample banks are statistically different from each other.

Table 9
Loan origination and career outcomes

Dep. var.: *Promotion* *Volume* defined by:	(1) Loan value	(2) Loan number
Volume	0.0069***	0.0268***
	(3.19)	(2.60)
Controls	Yes	Yes
Bank FE	Yes	Yes
Banker FE	Yes	Yes
Industry-year FE	Yes	Yes
Observations	7,585	7,585
Adj. R-squared	.1524	.1520

This table examines the relation between loan origination and favorable career outcomes. The dependent variable is *Promotion*, an indicator variable that equals one if a banker (a) exits a bank and moves to a larger bank or (b) accepts a higher position at the current bank in a given year, and zero otherwise. In Column 1, loan volume is measured based on the log total dollar value of loans originated in the past 3 years. In Column 2, volume is measured based on the natural log of the total number of loans originated in the past 3 years. The appendix defines the variables in detail. Standard errors are clustered by bank-year, and t-statistics are presented in parentheses. *$p<.1$; **$p<.05$; ***$p<.01$.

require this skill. Overall, the job postings suggest that bankers are expected to perform a variety of tasks, including originating loans, prospecting new business, and monitoring existing borrowers' loan quality.

From a theoretical perspective, one can view bankers' tasks through the lens of a classical multitasking model (e.g., Holmström and Milgrom 1991). These models predict that an agent facing two noncomplementary tasks will exert more effort on the task that is more easily measurable and explicitly rewarded. This argument can extend naturally to corporate bankers, as origination volume can be easily quantified and rewarded in the short run while loan quality is less observable, especially at issuance. The importance of loan volume to a banker's career also explains why many bankers explicitly advertise the size of their loan portfolio on their LinkedIn profiles.

Next, we conduct an analysis to provide more formal evidence on how bankers are rewarded for loan origination. Specifically, we test whether higher levels of loan volume are associated with career benefits for corporate bankers in our sample. We construct an indicator variable, *Promotion*, that equals one if a banker receives a higher title in her current bank (i.e., an internal promotion) or moves to a larger bank with at least an equivalent title (i.e., external promotion), and zero otherwise. We then regress *Promotion* on the level of loan volume originated by a banker in the prior 3 years. The model includes the same set of controls from our turnover analyses (Equation (1)).

Table 9 presents the results from this analysis. Column 1 presents the results when a banker's loan volume is measured based on the natural log of the total dollar volume s/he originated in the prior 3 years. Column 2 presents the results when banker volume is measured based on the natural log of total number of deals originated in the prior 3 years. In both analyses, the results indicate that higher origination volume is associated with a greater chance of upward career movements. This is consistent with bankers being rewarded for loan origination. In terms of economic magnitude, the results in Column 1 indicate that a 1-standard-deviation increase in dollar loan volume is associated with a 1.9 percentage point increase in promotion (the standard deviation of loan volume is 2.72). The results in Column 2 indicate that a 1-standard-deviation increase in deal volume is associated with a 1.8 percentage point increase in promotion (the standard deviation of deal volume is 0.67). This result is economically meaningful given that the average annual promotion rate is 7.95 percentage points. This result strengthens our claim that bankers face conflicting tasks that lead to risk-taking.

5.4 Alternative explanations

We argue that the body of evidence thus far is most consistent with banks disciplining bankers' risk-taking. In this section, we discuss alternative explanations for our findings. These alternatives fall into the following categories: (a) explanations based on economic conditions (such as mass layoffs); (b) explanations based on learning; and (c) explanations based on bankers' cohorts or individual experiences. We note that some of these alternative explanations are consistent with our main finding regarding credit events increasing banker turnover. However, these alternative explanations do not readily explain other results including (a) turnover being more pronounced for bankers with more lenient lending standards (Table 6, panel B) and (b) bankers issuing more conservative loans after experiencing credit events in their portfolios (Table 8).

5.4.1 Mass layoffs and economic conditions. A first alternative interpretation for our results is that time-varying macroeconomic or bank-specific conditions may explain the relationship between credit events and turnover. For example, mass layoffs at a bank or reduced business in a nonprofitable lending segment might relate to both credit events and turnover. While all of our tests include industry-year fixed effects to control for time-varying unobservable conditions, we also conduct analyses that explicitly remove recession periods from our sample. Column 1 of Table 10, panel A, presents this analysis. Our result persists in nonrecessionary periods with a stronger magnitude than the one produced by the baseline analysis.

We further consider whether our findings are due to bank-specific distress, as banks experiencing deteriorating performance (e.g., higher levels of default) should have the greatest incentive to shrink their workforce. In Column 2 of Table 10, panel A, we examine a subsample in which a corporate banking department has low levels of default (i.e., less than 0.5% defaults in a given year). Credit events remain positively and significantly associated with turnover in this sample, suggesting our results are not unduly influenced by a bank's poor performance. More broadly, we consider the possibility that time-varying characteristics of a bank (e.g., changes in lending policy, culture, management) may explain our findings. We augment our model with bank-year fixed effects

Table 10
Alternative explanations

A. Bank conditions

Dep. var.: *Exit*	(1)	(2)	(3)
Sample:	Nonrecession	Low default	Full
Credit event	0.0410***	0.0356**	0.0267**
	(2.97)	(2.11)	(2.14)
Controls	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes
Bank FE	Yes	Yes	No
Banker FE	Yes	Yes	Yes
Bank-year FE	No	No	Yes
Observations	4,934	3,560	7,585
Adj. R-squared	.2422	.2025	.2339

B. Bank learning

Dep. var.: *Lending term*	(1)	(2)
Lending term:	*Covenants*	*Strictness*
Credit event	0.7132**	0.2066***
	(2.38)	(3.36)
Peer credit event	−0.1446	0.0144
	(−0.55)	(0.18)
Controls	Yes	Yes
Loan type FE	Yes	Yes
Industry-year FE	Yes	Yes
Bank FE	Yes	Yes
Banker FE	Yes	Yes
Observations	2,947	2,100
Adj. R-squared	.7933	.8518

C. Cohort effects

Dep. var.: *Exit*	(1)	(2)	(3)	(4)	(5)
Credit event	0.0252**	0.0272**	0.0316**	0.0287***	0.0219*
	(2.42)	(2.05)	(2.53)	(2.73)	(1.93)
*Credit event **		0.0061			
Enter in crisis		(0.28)			
Controls	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes
Banker FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes			
Cohort-year FE	Yes				
Bank-bank entrance FE			Yes		
Bank-cohort FE				Yes	
Bank-portfolio size FE					Yes
Observations	7,585	7,585	7,585	7,585	7,585
Adjusted R-squared	.2109	.1927	.0498	.0504	.0527

This table tests the plausibility of various alternative explanations for our turnover results. Panel A examines how economic conditions influence the relation between credit events and banker turnover. Column 1 examines a sample of nonrecession years defined based on NBER Recession Dates. Column 2 examines periods of high performance based on the loan default rates for each bank-year. Column 3 examines the full sample and includes bank-year fixed effects. Panel B considers bank learning as an alternative explanation. We augment the loan term regression (Equation (5)), with an indicator variable for whether the banker's colleague in the same industry group has a credit event (*Peer credit event*). Panel C considers cohort effects by varying the inclusion of cohort-year interactive fixed effects, bank-bank entrance interactive fixed effects, bank-cohort interactive fixed effects, bank-portfolio size interactive fixed effects, and controls for crisis year cohorts (*Enter in crisis*). Additional details on these tests are provided in Section 5.4. The appendix defines the variables in detail. Standard errors are clustered by bank-year, and t-statistics are presented in parentheses. $*p<.1$; $**p<.05$; $***p<.01$.

and present these results in Column 3 of Table 10, panel A. Our results continue to persist, suggesting that time-varying bank characteristics do not explain our results. Overall, the evidence in panel A of Table 10 continues to indicate a positive and significant relationship between credit events and banker turnover, after further considering other economic conditions.

5.4.2 Learning. Our baseline turnover finding is consistent with predictions from a career concerns framework; that is, the employer learns about an employee's type from his or her output and punish the individual for underperformance. In Table 8, we also provide corroborating evidence that bankers tighten their lending standards when motivated by career concerns. An alternative explanation for this finding is that it simply reflects banks' learning about how to underwrite loans from credit events.

In Table 10, panel B, we design a test to evaluate the plausibility of the above explanation. Specifically, we test the effect of peer credit events (i.e., credit events occurring in the same year to other bankers working in the same bank and covering the same industry as the banker of interest) on a banker's future lending standards. If changes in lending standards are purely driven by the bank learning about how to write loans, one should expect the bank to require a banker to update his or her lending standards following any credit event, including the banker's own events and peer events. We reestimate Equation (5) and augment the model with the variable *Peer credit event*, an indicator that equals one if a different banker in the same bank and covering the same industry has a credit event, and zero otherwise. Column 1 provides the results for *Covenants*, and Column 2 provides the results for *Strictness*. We do not find any evidence that peer credit events are associated with changes in lending terms. Moreover, *Credit event* continues to load significantly with similar economic magnitudes as our baseline model after controlling for *Peer credit event*. These results suggest that bankers change their lending behavior primarily in response to their own credit events, and that the effect is unlikely to be driven by an overall change in the bank's lending practices.

5.4.3 Cohort analyses. Next, we consider how a banker's cohort influences his or her loan performance and career trajectories. We control for cohort effects in several ways in panel C of Table 10.

First, we consider the possibility that the year in which a banker starts his (her) career (i.e., his or her cohort) influences the likelihood that the banker will remain at the bank. To account for this possibility, we define a cohort as the group of bankers that enter the banking labor market during the same year and include a set of banker's cohort interacted with year fixed effects in Column 1 (i.e., Cohort-Year interactive fixed effects). We continue to document a positive and significant loading on *Credit event*.

Next, we examine whether bankers that started their careers during crisis times have a differential likelihood of exiting from their banks. In Column

2, we follow NBER and define crisis periods as 1990–1991, 2001, and 2007–2009 and then examine regressions of *Exit* on the interaction of *Credit event* with an indicator variable for whether a banker starts his or her career during a crisis period (*Enter in crisis*). While *Credit event* continues to load positively and significantly, the interaction term, *Credit event * Enter in crisis,* is insignificant, suggesting that crisis cohorts do not exhibit differential patterns in exit likelihood.

Third, we consider the possibility that a banker's career experience may affect the banker's likelihood to exit. In Column 3, we investigate this case by including interactive fixed effects for a bank and the year that a banker enters the specific bank (bank-bank entrance interactive fixed effects). This set of fixed effects controls for heterogeneity in institution-specific experiences among bankers, and thus helps narrow down the comparison among bank colleagues that enter the bank during the same year. In Column 4, we control for interactive fixed effects for a bank and its bankers' cohorts (bank-cohort interactive fixed effects). This analysis allows us to compare colleagues that have similar years of experience in their overall careers, regardless of which bank they enter in for their first job. Finally, we also compare bankers with similar levels of deal-making experience. We do so by including bank-portfolio size interactive fixed effects in Column 5. Across Columns 3 through 5, we continue to document positive and significant effects on *Credit event*. In the Internet Appendix, we further examine the sensitivity of our results to using a Cox Hazard model and produce similar inferences. We also control for interactive effects of cohort and time periods and find similar results. Overall, our evidence suggests that the relationship between credit events and turnover does not vary based on cohort effects.

5.5 Sampling issues

A final concern for our analyses relates to the data we use to identify corporate bankers and their career paths. With respect to the SEC documents, some loan contracts may be omitted from SEC filings if they are deemed "not material" to the firm of interest. With respect to LinkedIn, our data may be subject to limitations if profiles are missing. We conduct four analyses to help alleviate concerns related to our sample.

First, we design a test to reduce concerns that SEC documents may omit some loan contracts. To do so, we construct a backfilled sample assigning a banker to all of the loans issued to his or her primary industry within the bank, regardless of whether the SEC document identifies the loan. Using SEC documents, we first identify a banker's primary industry of specialization as the industry in which the banker issues the highest number of loans or loans with the highest value during his or her tenure at a given bank. Next, we assign to the banker all DealScan loans extended to that industry by that bank during the banker's employment. This procedure relies on the assumption that the banker works in a team focusing on a given industry segment, and that he or she would have some

Table 11
Credit events and banker turnover: Alternative samples

Dep. var.: *Exit*	(1)	(2)	(3)	(4)
Sample:	Industry backfilled	Active LinkedIn	SEC only	FINRA
Credit event	0.0217**	0.0324**	0.0364*	0.0240***
	(2.34)	(2.54)	(1.83)	(4.11)
Controls	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Banker FE	Yes	Yes	Yes	Yes
Observations	7,585	5,756	5,574	4,272
Adj. R-squared	.1927	.1860	.5130	.1644

This table examines how sample selection choices influence the relation between credit events and banker turnover. Column 1 considers an industry backfilled sample in which bankers are assigned to all loans in a given industry-year. Column 2 requires the banker to have an active profile (i.e., the subsample of bankers that transition to another employer at a later date or update their position at the bank of interest). Column 3 identifies movements using only data from SEC loan contracts. Column 4 uses an alternative career data set obtained from FINRA. The appendix defines the variable in detail. Standard errors are clustered by bank-year, and t-statistics are presented in parentheses. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

influence over the lending decision made by the team for that industry even if we cannot obtain all of the relevant SEC loan contracts. In the assignment process, we also only include the years that we can observe the banker having at least one outstanding loan in his or her portfolio (i.e., actively involved in lending activities). Column 1 of Table 11 reports the results using the industry-backfilled sample. Our results persist in this sample and indicate that *Credit Events* are associated with higher departure likelihood by 2.17 percentage points. This effect is similar in magnitude to our baseline finding, thus indicating that firms' discretion in disclosing credit agreements is unlikely to affect our results.

Our remaining sampling analyses focus on issues with LinkedIn. A primary concern here is that bankers who have been terminated may exercise caution in reporting prior job experiences. At the same time, employees are aware that reporting large gaps in one's work history can also be costly. As a result, it is unclear whether this issue poses a threat to our analyses.

In our first analysis addressing this issue, we reexamine our baseline analyses for a subset of active LinkedIn profiles. We consider a banker to be actively maintaining his or her profile in a given year if we observe the banker to have reported a new employer or new role at the bank of interest before the end of the sample period and after the credit event. This requirement ensures that corporate bankers do not stop reporting on LinkedIn after having a default event. Column 2 of Table 11 reports the results from this subsample. The evidence continues to suggest that credit events are associated with banker exits, suggesting that the noise generated by self-reporting of profiles is unlikely to drive such a relationship.

Next, we reexamine the association between credit events and banker exits using only data from the SEC contracts. Although these data are sparse, we can still identify employment changes if we observe at least two contracts from the same banker affiliated with different banks. To reduce the possibility that we do not observe an interim job span, we require movers to have a subsequent contract within 3 years of the previous contract date. The benefit of this analysis is that it removes issues related to self-reporting on LinkedIn. Column 3 of Table 11 provides the results from this analysis. Within this sample, we continue to find a positive and significant relationship between credit events and banker turnover and that the economic magnitudes are consistent with the baseline analyses.

In our last analysis related to sampling issues, we consider an alternative data set to LinkedIn. Following recent work by Egan, Matvos, and Seru (2019), we manually collect 1,174 profiles from the Financial Industry Regulatory Authority's (FINRA) *BrokerCheck* service for eligible bankers. FINRA is a self-regulatory agency that maintains public records of broker-dealers' enforcement actions, as well as 10 years of employment history. Some bankers in our sample are registered with FINRA as they obtained securities licenses and are thus required to register with FINRA.[22] We collect profiles for this subset of bankers through the FINRA *BrokerCheck* platform. In Column 4 of Table 11, we reexamine our results using a reconstructed employment panel based on FINRA data only. Our inferences remain unchanged using this panel and continue to illustrate the positive association of exits with credit events.

Overall, our analyses of sampling issues suggest that potential biases that may arise from the limited sample of SEC agreements and self-reporting on LinkedIn do not seem to influence our inferences. Across various alternative sampling procedures and data sources, we continue to document a positive and significant relationship between credit events and turnover with consistent economic magnitudes.

6. Conclusion

This study examines whether corporate bankers responsible for structuring large syndicated loans face career consequences following loan failures. The corporate banking sector presents a setting in which both banks and bankers face strong incentives to grow their loan portfolios and generate profit, potentially at the expense of loan quality. Examining the association between banker turnover and credit events helps reveal banks' preferences for credit risk and sheds light on their internal practices in managing employee risk-taking.

We collect data on the career paths, loan origination, and loan performance related to a large sample of corporate bankers employed by major U.S. banks over the period spanning 1994-2012. We find that credit events in a banker's portfolio (i.e., ratings downgrades, defaults, and bankruptcies) increase the

[22] Many bankers do not have FINRA profiles, as the SEC exempts certain banks from registering as broker-dealers under Sections 3(a)(4)(B) and 3(a)(5)(C) of the Exchange Act. Specifically, an exemption from the definition of "dealer" applies if a bank buys and sells certain "identified banking products" including letters of credit and bank loans. The document also states that the exemption applies if banking products are sold to "qualified investors" who "have the opportunity to review and assess material information." These exemptions seem highly relevant to the lenders in our sample. Although some bankers may obtain securities licenses because they engage in other securities activities that require registration (e.g., sale of other investment products), we do not believe that this is a universal requirement.

likelihood that the banker departs his or her current place of employment. Bankers also tighten their lending standards by imposing more stringent covenant packages on future loans. These results are consistent with the argument that banks punish bankers for risk-taking and that bankers' career concerns motivate them to tighten lending standards.

Our study adds to a growing literature examining the role of employee disciplining in the financial sector (e.g., Griffin, Kruger, and Maturana 2019; Egan, Matvos, and Seru 2019). We complement prior research by offering evidence on how banks manage credit risk exposure in their lending activities. In particular, our findings suggest that banks actively impose strict disciplining consequences for risk-taking in the corporate lending sector. These findings thus offer implications for regulators and policy makers, who have expressed concerns regarding inadequate risk management practices following the global financial crisis.

Appendix. Variable Definitions

Career outcomes	
Exit	An indicator variable equal to one if a banker departs a bank in a given year, and zero otherwise
Move down	An indicator variable equal to one if a banker departing a bank moves to a less desirable job, and zero otherwise. See Table 7 for classifications of *Move down*
Move up	An indicator variable equal to one if a banker departing a bank moves to a more desirable job, and zero otherwise. See Table 7 for classifications of *Move up*
Lending outcomes	
Covenants	The total number of covenants specified on a loan package
Strictness	The covenant strictness of the loan package that indicates the probability of a covenant violation. This measure is calculated using the methodology specified in Murfin (2012)
Credit events	An indicator variable equal to one if at least one borrower in a banker's portfolio
Downgrades	experiences a ratings downgrade by S&P in the current or prior year, and zero otherwise
Default	An indicator variable equal to of one if at least one borrower in a banker's portfolio receives a default rating from S&P ("D" or "SD") or files for bankruptcy in the current or prior year, and zero otherwise
Credit event	An indicator variable equal to one if at least one borrower in a banker's portfolio experiences a downgrade or default (defined above) in the current or prior year, and zero otherwise
Bank turnover beta	Coefficient estimates from regressing banker turnover on lead arranger credit event performed at the bank level. The regression controls for banker fixed effects and industry-year fixed effects
Origination	
Loan value	The natural log of the total dollar value of loans originated by a banker in the prior 3 years
Loan number	The natural log of the total number of loans originated by a banker in the prior 3 years
Controls	
Loan spread	The portfolio average of total all-in drawn spreads over LIBOR for a banker's outstanding loans
Loan size	The portfolio average of loan size (the natural log of the loan) for a banker's outstanding loans
Loan maturity	The portfolio average of loan maturity (in years) for a banker's outstanding loans
Time since origination	The portfolio average number (in years) until loan maturity for a banker's outstanding loans

Portfolio size	The total number of loans in a banker's portfolio
Comparable spreads	The average spreads specified on comparable loan contracts, where comparable loans are defined as loans issued in the past year to borrowers in the same 2-digit SIC industry with similar characteristics (e.g., same ratings category, similar distance-to-default, or same loan maturity range)
Comparable covenants	The average number of covenants specified on comparable loan contracts, where comparable loans are defined as loans issued in the past year to borrowers in the same 2-digit SIC industry with similar characteristics (e.g., same ratings category, similar distance-to-default, or same loan maturity range)
Comparable strictness	The average level of covenant strictness specified on comparable loan contracts, where comparable loans are defined as loans issued in the past year to borrowers in the same 2-digit SIC industry with similar characteristics (e.g., same ratings category, similar distance-to-default, or same loan maturity range)
Size	The natural log of the borrower's total assets
Capital expenditures	Capital expenditures scaled by total assets
Market-to-book	The borrower's market to book ratio, calculated as stock price X shares outstanding plus total assets less book value of equity, scaled by total assets
Cash holdings	Cash and cash equivalent scaled by total assets
Profitability	The borrower's operating income scaled by total assets
Tangibility	The borrower's total value of property, plant, and equipment, scaled by total assets
Rated dummy	A dummy variable indicating whether a borrower has a credit rating outstanding

References

Acharya, V., and H. Naqvi. 2012. The seeds of a crisis: A theory of bank liquidity and risk taking over the business cycle. *Journal of Financial Economics* 106:349–66.

Adrian, T., and H. S. Shin. 2010. Liquidity and leverage. *Journal of Financial Intermediation* 19:418–37.

Allen, F., and R. Herring. 2001. Banking regulation versus securities market regulation. Working Paper, Wharton Business School.

Baron, M., and W. Xiong. 2017. Credit expansion and neglected crash risk. *Quarterly Journal of Economics* 132:713–64.

Benmelech, E., J. Dlugosz, and V. Ivashina. 2012. Securitization without adverse selection: The case of CLOs. *Journal of Financial Economics* 106:91–113.

Berg, T. 2015. Playing the devil's advocate: The causal effect of risk management on loan quality. *Review of Financial Studies* 28:3367–406.

Berg, T., M. Puri, and J. Rocholl. 2016. Loan banker incentives and the limits of hard information. Working Paper, Frankfurt School of Finance & Management.

Berger, A. N., and G. F. Udell. 2004. The institutional memory hypothesis and the procyclicality of bank lending behavior. *Journal of Financial Intermediation* 13:458–95.

Bushman, R. M., J. Gao, X. Martin, and J. Pacelli. 2019. The influence of loan officers on debt contract design and performance. Working Paper, University of North Carolina, Chapel-Hill.

Chava, S., and M. R. Roberts. 2008. How does financing impact investment? The role of debt covenants. *Journal of Finance* 63:2085–121.

Cheng, I. H., S. Raina, and W. Xiong. 2014. Wall street and the housing bubble. *American Economic Review* 104:2797–829.

Chevalier, J., and G. Ellison. 1999. Career concerns of mutual fund managers. *Quarterly Journal of Economics* 114:389–432.

Chodorow-Reich, G. 2014. The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis. *Quarterly Journal of Economics* 129:1–59.

Clifford, C. P., and W. C. Gerken. 2017. Investment in human capital and labor mobility: Evidence from a shock to property rights. Working Paper, University of Kentucky.

Deming, D., and L. B. Kahn. 2018. Skill requirements across firms and labor markets: Evidence from job postings for professionals. *Journal of Labor Economics* 36:S337–S369.

Egan, M., G. Matvos, and A. Seru. 2019. The market for financial adviser misconduct. *Journal of Political Economy* 127:233–95.

Ellul, A., M. Pagano, and A. Scognamiglio. 2020. Career risk and market discipline in asset management. *Review of Financial Studies* 33:783–828.

Ellul, A., and V. Yerramilli. 2013. Stronger risk controls, lower risk: Evidence from US bank holding companies. *Journal of Finance* 68:1757–803.

Engelberg, J., Gao, P., and Parsons, C. A. 2012. Friends with money. *Journal of Financial Economics* 103:169–88.

Ernst and Young. 2014. Shifting focus: Risk culture at the forefront of banking. 2014 Risk management survey of major financial institutions. Report, Ernst and Young, London, UK. https://www.ey.com/Publication/vwLUAssets/ey-shifting-focus-risk-culture-at-the-forefront-of-banking/$File/ey-shifting-focus-risk-culture-at-the-forefront-of-banking.pdf

Fahlenbrach, R., R. Prilmeier, and R. M. Stulz. 2017. Why does fast loan growth predict poor performance for banks? *Review of Financial Studies* 31:1014–63.

Fahlenbrach, R., and R. M. Stulz. 2011. Bank CEO incentives and the credit crisis. *Journal of Financial Economics* 99:11–26.

Federal Reserve. 2011. Incentive compensation practices: A report on the horizontal review of practices at large banking organizations. Report, Federal Reserve, Washington, DC. https://www.federalreserve.gov/publications/other-reports/incentive-compensation-report-201110.htm

Gibbons, R. 1996. Incentives and careers in organizations. Working Paper, Massachusetts Institute of Technology.

Gibbons, R., and K. J. Murphy. 1992. Optimal incentive contracts in the presence of career concerns: Theory and evidence. *Journal of Political Economy* 100:468–505.

Gopalan, R., V. Nanda, and V. Yerramilli. 2011. Does poor performance damage the reputation of financial intermediaries? Evidence from the loan syndication market. *Journal of Finance* 66:2083–120.

Graham, J. R., S. Li, and J. Qiu. 2008. Corporate misreporting and bank loan contracting. *Journal of Financial Economics* 89:44–61.

Greenwald, B. C. 1986. Adverse selection in the labour market. *Review of Economic Studies* 53:325–47.

Griffin, J. M., S. Kruger, and G. Maturana. 2019. Do labor markets discipline? Evidence from RMBS bankers. *Journal of Financial Economics* 133:726–50.

Herpfer, C. 2018. The role of bankers in the US syndicated loan market. Working Paper.

Hershbein, B., and L. B. Kahn. 2018. Do recessions accelerate routine-biased technological change? Evidence from vacancy postings. *American Economic Review* 108:1737–72.

Hertzel, M. G., Z. Li, M. S. Officer, and K. J. Rodgers. 2008. Inter-firm linkages and the wealth effects of financial distress along the supply chain. *Journal of Financial Economics* 87:374–87.

Hertzel, M. G., and M. S. Officer. 2012. Industry contagion in loan spreads. *Journal of Financial Economics* 103:493–506.

Hida, E., and J. Leake. 2015. Risk advisory: The future of risk in financial services. Report, Deloitte, London, UK. https://www2.deloitte.com/content/dam/Deloitte/global/Documents/Financial-Services/gx-global-RA-Future-of-Risk-POV.pdf

Holmström, B. 1999. Managerial incentive problems: A dynamic perspective. *Review of Economic Studies* 66:169–82.

Holmström, B. and P. Milgrom. 1991. Multitask principal-agent analyses: Incentive contracts, asset ownership, and job design. *Journal of Law, Economics, & Organization* 7:24–52.

Hong, H., and J. Kubik. 2003. Analyzing the analysts: Career concerns and biased earnings forecasts. *Journal of Finance* 58:313–51.

Irani, R. M., and R. R. Meisenzahl. 2017. Loan sales and bank liquidity management: Evidence from a US credit register. *Review of Financial Studies* 30:3455–501.

Ivashina, V. 2009. Asymmetric information effects on loan spreads. *Journal of Financial Economics* 92:300–319.

Jacobson, L. S., R. J. LaLonde, and D. G. Sullivan. 1993. Earnings losses of displaced workers. *American Economic Review* 1:685–709.

Kashyap, A. K. 2010. Lessons from the financial crisis for risk management. Financial Crisis Inquiry Commission.

Kashyap A. K., R. G. Rajan, and J. C. Stein. 2008. Rethinking capital regulation. Report, Kansas City Federal Reserve, Kansas City, MO. https://www.kansascityfed.org/media/files/publicat/sympos/2008/kashyaprajanstein031209.pdf

Lin C., Y. Ma, P. Malatesta, and Y. Xuan, 2011. Ownership structure and the cost of corporate borrowing. *Journal of Financial Economics* 1:1–23.

Lookman, A. A. 2009. Bank borrowing and corporate risk management. *Journal of Financial Intermediation* 18:632–49.

Murfin, J. 2012. The supply-side determinants of loan contract strictness. *Journal of Finance* 67:1565–601.

Murfin, J., and R. Pratt. 2018. Comparables pricing. *Review of Financial Studies* 32:688–737.

Petersen, M. A. 2004. Information: Hard and soft. Working Paper, Northwestern University.

Roberts, M. R. 2014. The role of dynamic renegotiation and asymmetric information in financial contracting. *Journal of Financial Economics* 116:61–81.

Roberts, M. R., and A. Sufi. 2009. Renegotiation of financial contracts: Evidence from private credit agreements. *Journal of Financial Economics* 93:159–84.

Ross, D. G. 2010. The 'dominant bank effect': How high lender reputation affects the information content and terms of bank loans. *Review of Financial Studies* 23:2730–56.

Şahin, A., J. Song, G. Topa, and G. L. Violante. 2014. Mismatch unemployment. *American Economic Review* 104:3529-64.

Shleifer, A., and R. Vishny. 2011. Fire sales in finance and macroeconomics. *Journal of Economic Perspectives* 25:29–48.

Sufi, A. 2007. Bank lines of credit in corporate finance: An empirical analysis. *Review of Financial Studies* 22:1057–88.

UBS. 2016. Operational Risk Awards 2016: Bank of the year. Risk.net. July/August 2016:1–3. https://www.ubs.com/global/en/about_ubs/about_us/awards/group/_jcr_content/par/textimage_2063176531.1154302463.file/dGV4dD0vY29udGVudC9kYW0vc3RhdGljL2dsb2JhbC9hYm91dF91YnMvYXdhcmRzL3Jpc2stbmV0LXVicy5wZGY=/risk-net-ubs.pdf

Washington, G. 2010. Stiglitz: We have to throw bankers in jail or the economy won't recover. *Business Insider: Washington's Blog*, November 4. https://www.businessinsider.com/nobel-economist-says-we-have-to-prosecute-fraud-or-else-the-economy-wont-recover-2010-11

Whitehead, C. K. 2008. The evolution of debt: Covenants, the credit market, and corporate governance. *Journal of Corporate Law* 34:641–76.

Wittenberg-Moerman, R. 2008. The role of information asymmetry and financial reporting quality in debt trading: Evidence from the secondary loan market. *Journal of Accounting and Economics* 46:240–60.