Do Loan Officers Impact Lending Decisions? Evidence from the Corporate Loan Market*

Janet Gao	Xiumin Martin	Joseph Pacelli
Indiana University	*Washington University at St. Louis*	*Indiana University*
janetgao@indiana.edu	xmartin@wustl.edu	jpacelli@indiana.edu

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Abstract

We examine and quantify the economic importance of loan officers in the corporate lending process. We construct a comprehensive database that allows us to track the lending terms and loan performance of corporate loans issued by over 7,000 loan officers employed by major U.S. corporate lending departments during the period spanning from 1994 to 2012. We find that loan officers have a substantial impact on both the contract terms (loan spreads, covenants, and maturity) and the performance of corporate loans. The results are robust to controlling for endogeneity concerns related to assortative matching in the labor market. Loan officers' influence on the lending process has not declined much over time, despite technological innovations designed to automate lending. Furthermore, these officers exhibit a greater impact on the lending process in larger, more complex organizations in which information asymmetries are more pronounced. Overall, our study sheds light on the inner workings of corporate banking departments and suggests that a significant portion of lending decisions are delegated to individual loan officers.

Key words: Loan Officers, Human Capital, Syndicated Loans, Loan Contracts.

JEL classification: G30, G32, J24, D23

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1 Introduction

A central objective of banks is to collect and process information (Petersen (2004)). Accordingly, theoretical studies argue that banks, compared to bond investors, are superior at producing information about their borrowers, especially when that information is not publicly observable (Diamond (1984, 1991), Ramakrishnan and Thakor (1984)). Rapid consolidation in the banking industry coupled with technological advancements have potentially reshaped the information production processes underlying many lending decisions (Petersen and Rajan (2002)). Within these modern organizations, loan officers at lower tiers are typically responsible for collecting information about borrowers and transmitting this information to managers of the bank (Stein (2002)). However, with the existence of multiple layers and advanced technology within a bank, it is not clear where the final decision rights reside between the headquarters and loan officers.

In this study, we examine and quantify the relative importance of individual loan officers compared to their institutions in setting loan terms and influencing loan performance. Our goal is to shed light on how information is produced and used in banks' lending decisions. Ultimately, banks face a trade-off between complete delegation, where lower-tiered agents (such as loan officers) make final lending decisions, and centralization, where decision rights are concentrated completely at headquarters. Too much delegation could lead to information manipulation due to loan officers having misaligned incentives and facing costly communication (Stein (2002), Dessein (2002), Agarwal and Hauswald (2010), Gropp et al. (2012), Brown et al. (2012)), while too little delegation could result in the loss of valuable soft information regarding the banks' borrowers. With improvements in lending technology and financial reporting quality, recent research suggests that banks may be able to rely more on hard information (Petersen and Rajan (2002), Berger et al. (2005)). As such, it remains unknown how much decision rights are delegated to loans officers. This study seeks to bridge this gap by piercing the "black box" of banks' corporate lending activities.

We focus on the market for corporate loans, as it represents an important source of financing for corporations and a major service provided by banks (Roberts (2015)).

Moreover, corporate lending contains significant information asymmetries between banks and their borrowers, thus providing a setting in which loan officers' judgment may be a valuable asset for banks. Traditionally, data on the identities of loan officers issuing corporate loans are not readily available, making it difficult for researchers to distinguish the effect of the loan officer on the lending process from that of the bank. To overcome this data challenge, we collect and analyze 4,215 loan agreements from SEC filings in which we identify the loan officers underwriting these contracts. We then supplement these SEC documents using loan contract terms provided by LPC Dealscan. To our knowledge, this represents one of the most comprehensive databases on U.S. loan officer employment as it contains 7,892 loan officers working in major U.S. corporate lending departments from 1994 to 2012. These officers issue nearly $1.8 trillion in financing to 1,678 corporate borrowers over our sample period. Importantly, our dataset allows us to observe loan officers at different points of employment over their careers and to track the lending terms and loan performance related to a particular loan officer as she moves across banks.

Our objective is to identify and quantify the effects of loan officers in the lending process. To this end, we exploit loan officer turnover as an important source of variation to estimate loan officer fixed effects. We employ empirical methods developed by Abowd, Kramarz, and Margolis (1999) and Abowd, Creecy, and Kramarz (1999) that allow the estimation of individual effects in large panel data (hereafter, AKM method). This methodology identifies bank fixed effects using changes in lending outcomes associated with loan officers moving between banks, and identifies loan officer fixed effects by removing the estimated bank fixed effects from individual loan outcomes. Following recent research distinguishing the effects of institutions and individuals in labor market settings (e.g., Graham et al. (2012), Ewens and Rhodes-Kropf (2015), Liu et al. (2016)), we adopt this methodology to quantify the extent to which loan officers influence lending processes within corporate lenders.

Our analyses reveal an economically important role of loan officers in the lending process. We first estimate loan officers' impact on three common lending terms: loan spread, loan covenant, and loan maturity. We find that loan officers explain a substantial portion of the variation in lending terms. For example, loan officer effects explain approximately 24% of the variation in loan spreads. Relatively speaking, loan officer effects explain about five times as much variation in loan spreads as do bank fixed effects. These results suggest that loan officer fixed effects are economically significant in both an absolute and relative sense. Similarly, loan officers explain five times more variation in loan covenants and nine times more variation in loan maturity than do banks. These findings are robust to controlling for observable characteristics of the borrower and loan contracts. This initial analysis thus suggests an important role of loan officers in setting corporate lending terms.

As loan officers are delegated with significant power in designing loan contract terms, it is natural to conjecture that their influence will have implications for future loan performance. Therefore, our next set of analyses examines loan officers' effects on loan performance, as measured by future borrower defaults, downgrades, and accounting performance (i.e., ROA). The evidence from these tests confirms this conjecture. For example, our estimates suggest that loan officer fixed effects explain 47% of the variation in future borrower default, which is much greater than the variation explained by other borrower and loan characteristics combined. In addition, loan officers explain over 13 times more variation in the occurrence of defaults in loan portfolios than do banks alone. We generate similar inferences using other measures of performance. Taken together, the evidence from our main analyses suggests that loan officers play an important role in both setting lending terms and influencing loan performance.

Before proceeding, it is critical to note that the estimation techniques we employ rely on non-random loan officer movement, and that these methods can admit potential endogeneity concerns. Indeed, these concerns represent a limitation common to all studies relying on employee movement as a source of variation (Graham et al. (2012), Ewens and Rhodes-Kropf (2015), Liu et al. (2016)). Outside of experimental settings, it is difficult to perfectly isolate employee effects due to the scarcity of exogenous movement. Research must inevitably face a trade-off between the loss of precision available in experimental settings, and the gains associated with generalizable, large-scale evidence of economic phenomena. We view our study as a complement to prior experimental research on loan officers' behavior (e.g., Liberti and Mian (2009), Agarwal and Ben-David (2014)). We extend this line of research by quantifying the effects of loan officers in an important lending market across a long time span and a wide-spectrum of banks. At the same time, we are cognizant of the limitations of our analysis. We conduct a battery of robustness tests to address these concerns in turn.

First, we address a common issue associated with the AKM methodology in that individual fixed effects may be over-estimated when we only observe limited movement in the sample. With movers comprising 17% of our sample, our data structure is unlikely to introduce significant biases in our findings.[1] Nevertheless, we re-examine our analysis by restricting our sample to only movers (i.e., loan officers that can be observed in at least two banks during the sample period). Using this subsample, we directly compare the incremental R^2 attributed to loan officer fixed effects and bank fixed effects.[2] Even in this subsample restricted to movers, loan officers explain at least two to three times more variation in lending terms and loan performance than do bank fixed effects. This suggests that our inferences are unlikely to be biased by limited movement.

We next examine whether and to what extent assortative matching between loan officers and banks affects our findings (Becker (1973)). Assortative matching entails banks' tendency to hire loan officers with similar quality, risk preferences, or judgment. It is important to note that assortative matching does not always pose a challenge to our inferences as it often will result in loan officer fixed effects being under-estimated in the AKM framework. For example, if movement is a result of loan officers seeking positions in banks that have similar time-invariant characteristics related to their lending decisions (e.g., risk tolerance), the AKM method would over-estimate the bank's effect, which biases against our conclusion that loan officers matter in the lending process. Accordingly, we conduct detailed analyses and focus our attention on scenarios in which bank effects are

[1] This figure is also in line with prior studies using the AKM method (e.g., Graham et al. (2010), Ewens and Rhodes-Kropf (2015)).

[2] This method is commonly referred to as the mover-dummy-variable method (MDV).

likely under-estimated.

We begin by visually inspecting the severity of assortative matching in the data. To do so, we compute the variation in loan contract terms extended by all loan officers in a given bank-year, and compare this with the variation in loan contract terms generated by a randomly-selected, equal-sized group of loan officers employed across all banks in the same year. Our visual inspection of the variances suggests that assortative matching, although present, is not pronounced in our data. In some scenarios, the variation in loan contract terms extended by loan officers in our sample is almost indistinguishable from those generated by a randomly-selected group of loan officers.

Next, we examine whether time-varying lending policies across banks influence our findings. For example, a bank may change its lending policies over time and hire loan officers that are aligned with this new direction. This represents a concern because the movers we observe (i.e., newly hired loan officers) may exhibit similar lending preferences prior to the move as the lending policies at the bank of interest. In this case, one would under-estimate time-invariant bank effects using the AKM method. Accordingly, we control for banks' time-varying lending policies by including bank-year fixed effects in our baseline framework. Our findings continue to indicate that loan officers explain a large portion of the variation in lending terms and loan performance. This test also represents an important extension from prior studies examining individual fixed effects, as these studies generally do not have sufficient variation to control for time-varying preferences of the employer (e.g., Graham et al. (2012)).

We further consider scenarios in which we only observe movers between similar banks. Bank effects will be under-estimated in such scenarios since the original bank and destination bank of a given mover have similar lending policies. To alleviate this concern, we re-examine our analyses using a subsample of banks connected by loan officers that move to different categories of banks in terms of market share rankings (i.e., moving up or moving down in bank ranking). Our inferences remain unchanged in this subsample.

Finally, we consider additional matching concerns related to loan officers' selection of borrowers. Conceptually, we do not exclude the choice of borrowers from loan officers' lending decisions. Nonetheless, to better understand whether loan officers' choice of borrower influences our findings, we conduct an additional analysis that purges the choice of borrower from loan officers' lending decisions. To do so, we modify our baseline models by controlling for bank-firm pairings, which artificially attributes all the decision rights in borrower selection to banks. Our results continue to hold in this analysis, indicating that the non-random assignment of borrowers to loan officers does not explain our findings.

Overall, the battery of robustness tests we conduct verifies our baseline findings that loan officers play an important role in setting lending terms and influencing loan performance. Similar to prior studies, we recognize that the complexity of labor market matching creates endogeneity problems that cannot be completely addressed (Graham et al. (2012), Ewens and Rhodes-Kropf (2015)). Importantly, our tests offer several novel extensions to the prior literature. For example, by controlling for bank-year two-way interactive effects, we can alleviate to a large extent concerns regarding time-varying bank characteristics influencing our findings.

Our next analyses examine cross-sectional and time-series variation in the explanatory power of loan officer fixed effects. We first partition banks by the size and industry concentration of their loan portfolios, and find that loan officers explain a greater portion of the variation in lending terms and loan outcomes in banks with larger and more diverse loan portfolios. These findings suggest that complex organizations might benefit more from delegation, potentially due to the increased communication costs associated with transmitting soft information through organizational hierarchies and greater risks of information manipulation in that process. We next partition our sample into four time periods of similar sample size to investigate whether technological improvements have reduced banks' dependence on loan officers collecting soft information in the lending process (Rajan and Petersen (2002), Berger et al. (2005)). Loan officer effects explain a large portion of the variation in lending terms and loan performance across all subsamples, suggesting that either the corporate lending process is difficult to automate or the automation process continues to involve significant human judgment. Interestingly, we find that loan officers have a substantial effect on loan performance in the pre-crises years, consistent with the argument that agency problems were intensified prior to the crises.

Finally, having established evidence that loan officers play an important role in the corporate lending process, we conduct exploratory analyses to further understand the inter-relations and sources of loan officers' fixed effects. First, we correlate estimated loan officer fixed effects across different lending terms and loan performance to identify whether there are overarching patterns in loan officers' lending decisions. We find that loan officers who include more covenants in loan contracts tend to charge lower interest rates and shorten debt maturity. Officers also seem to pair high interest rates with long maturities. Importantly, we find that officers who consistently impose higher interest rates tend to issue riskier loans. These results suggest certain strategies in lending decisions. We further investigate whether loan officers' personal backgrounds contribute to this heterogeneity. We collect information regarding loan officers' educational background, gender, and place of first employment from *LinkedIn*. We find evidence suggesting that loan officers who studied at top tier schools tend to charge higher interest rates. In addition, officers that begin their career at large institutions are more likely to originate loans with short maturity and issue loans that perform poorly. However, these observable characteristics only explain a negligible portion of the variation in their lending decisions, suggesting that these decisions are likely attributable to other, unobservable factors.

Our study contributes to the literature in several ways. First, we provide the first large-sample evidence showing the role of individual loan officers in the corporate lending process. There is a burgeoning literature examining the role of loan officers and how they respond to various incentive schemes (e.g., Liberti and Mian (2009), Berg, Puri, and Rocholl (2013), Mosk (2014), Drexler and Schoar (2014), Degryse et al. (2014), Agarwal and Ben-David (2014), Cole et al. (2015), Karolyi (2017)).[3] However, these studies generally sample on foreign lending markets, different banking products, or focus on experimental settings inside a single bank. Our broad sample of loan officers enables us to examine and quantify the importance of loan officers in the corporate lending market.

[3]In a related study, Herpfer (2016) examines the role of soft information in lending relationships. His study focuses on the role of time-varying soft information and examines a smaller sample of loan officers employed primarily by lead banks.

Our finding that loan officers consistently play a significant role in the lending process over time complements studies that document changes in banks' reliance on soft information (Petersen and Rajan (2002), Berger and Udell (2004)).

Second, we contribute to a growing literature examining the relative importance of employees within a firm (e.g., Bertrand and Schoar (2003), Schoar and Zuo (2017), Graham, Li and Qiu (2012), Ewens and Rhodes-Kropf (2015), Liu et al. (2016)). These studies generally suggest that executives, fund partners, and inventors have significant influence over corporate decisions and performance. Our study contributes to this literature in two dimensions. First, our study is among the first to highlight the influence of lower-level employees inside large organizations, such as loan officers. Second, we focus on the function of those employees in financial intermediaries (Petersen 2004). The heterogeneity in the influence of loan officers we document reflects the varying degree of delegation across banks in the corporate lending market.

Finally, our study extends the literature examining corporate loan markets, in particular, studies documenting persistent lender characteristics affecting loan performance and contract terms (Billet, Flannery and Garfinkel (1995), Ross (2010), Gopalan, Nanda and Yerramilli (2011), Bushman and Wittenberg-Moerman (2012), Ellull and Yerramilli (2012)). Complementary to these studies, our study quantifies the explanatory power of the time-invariant dimension of loan officers' heterogeneities and compares that with the banks where these loan officers are employed. The main takeaway is that loan officers appear to play an economically meaningful role in the syndicated lending market.

This paper develops as follows: Section 2 describes our data source, variable construction, and empirical methodology. Section 3 describes the univariate patterns of our data. Section 4 provides our main results. Section 5 discusses and addresses the endogeneity concerns related to our findings. Section 6 exploits cross-sectional variation. Section 7 concludes.

2 Data & Empirical Methodology

2.1 Sample Selection

We begin our sample selection by retaining all loans issued on LPC Dealscan between the years 1994 and 2012. We start with a sample of 93,073 loans with information regarding contract terms, including spreads, covenants, and maturity. To be included in the sample, we require borrowers to have available financial information from Compustat. We further exclude borrowers in financial and utility industries as they generally have less comparable financial policies. This procedure leaves us with an initial sample of 41,977 loans extended to 4,446 firms.

2.2 SEC Filings

Based on the initial Dealscan sample, we search SEC filings for the official contracts related to these loans. Loan contracts are considered material public disclosures and are generally filed as Exhibits to firms' 8-K's, 10-Q's and 10-K's. In particular, we search for any public filing that contains an appended Exhibit 10 (which relates to "Material Contracts"). We further require the contract to contain either the word "loan" or "credit" followed by "agreement" in the title to ensure that the material contract we are extracting relates to a loan agreement, as opposed to other contracts (e.g., supply agreements, executive compensation agreements, etc.). We search for all filings meeting this criteria in the 90-day window centered on the loan initiation date observed in Dealscan. Doing so allows us to account for errors in the dates that Dealscan reports.[4]

A large proportion of loan agreements contain signature pages attached to the end of the agreement. These signature pages allow us to identify the names of loan officers. Accordingly, we require the documents in our sample to contain the string "/s/", which indicates that the document contains such a signature page. Following this symbol, we extract the name of the loan officer, the bank in which she is employed, and her title as shown in the signature page. This process results in a sample of 7,892 unique loan officers

[4] As noted in Murfin (2012), Dealscan sometimes reports loan dates at a lag due to delays related to banks approving term sheets and receiving mandates.

with 4,215 loan contracts, representing a 10% match to the original loan sample. While this sample may seem small, it is important to note that the SEC Edgar database was not complete for our entire sample period.

Before proceeding, it is important to discuss some assumptions and judgments we have to make with respect to our data collection process. First, we assume that loan officers who signed the loan contracts appended to SEC documents are the loan officers responsible for screening and monitoring the borrower. Per our discussion with an industry practitioner, syndicated loans are commonly written and monitored by a team consisting of a managing director or senior vice president, a loan officer and a credit analyst at each lead bank and participant bank. The managing director or senior vice president usually supervises the whole syndication team. The majority of loan officers in our sample have a title of "Vice President" (Figure 1). We therefore believe it is appropriate to attribute loan performance to these officers as they likely had some influence in the lending decision. Second, we identify loan officer turnovers by the dates and the affiliation listed on the loan contracts. We admit that this identification is imprecise. As such, we do not observe the exact timing that a loan officer transition between banks in her career. However, this limitation does not affect our empirical inferences because our unit of analysis is at the loan-bank-officer level.

2.3 Variables of Interest

2.3.1 Loan Terms

We examine three aspects of loan contract terms that prior studies consider to be important dimensions of the debt contracting process (e.g., Bharath et al. 2011, Chava and Roberts 2008). We first consider interest rate spreads (*Loan Spreads*), representing the markup charged by the lender (all-in-drawn spreads, in basis points over LIBOR). Next, we examine the total number of covenants included in a loan package (*Loan Covenants*). We also consider the maturity of the loan contract (*Loan Maturity*), measured as the number of months until the loan matures. These terms encompass both the pricing and non-pricing dimensions of a loan contract.

2.3.2 Loan Performance

We also examine three measures of loan performance. Our main measure is the occurrence of default. We define an indicator variable *Default* that takes the value of one if a borrower receives a default rating as per S&P ("D" or "SD") or files for bankruptcy before the loan matures, and zero otherwise. Albeit rare, defaults constitute the most extreme credit events that can occur in a lending portfolio. We thus use *Default* as the primary measure of loan performance. We also construct a supplementary, yet less extreme measure of loan performance: the extent of borrowers' downgrades (*Downgrade*). To construct this measure, we decode all S&P ratings from ($AAA = 1$, $AA+ = 2$,..., and D or $SD = 22$), and calculate the difference in ratings for the borrower from the loan initiation date to loan maturity. Downgrades suggest that borrowers are less likely to meet their debt obligations. Our final measure of loan performance is borrowers' average profitability over the course of the loan (*ROA*). Although it does not represent direct losses to lenders, borrowers' *ROA* provides a continuous metric that can reflect declines in future credit quality (Bushman and Wittenberg-Moerman (2011)).

2.3.3 Control Variables

We include control variables related to characteristics of the borrower and the loan contract (defined in Appendix A). Firm controls include *Size*, *Age*, *Profitability*, *Tangibility*, *M/B*, *Leverage*, and an indicator for whether a firm receives credit ratings (*Rated*). Loan controls include *Loan Spreads*, *Loan Covenants* and *Loan Maturity* when they are not examined as outcome variables. We also control for *Loan Size*, an indicator for whether the bank is a *Lead Arranger*, and loan type fixed effects (e.g., revolver, term loan A, term loan B, etc.). The models also include year and borrower industry fixed effects. We winsorize all continuous variables except leverage to 5^{th} and 95^{th} percentiles. We restrict *Leverage* to be within 0 and 1. Detailed definitions of these variables are described in Appendix A.

2.4 Loan Officer Fixed Effects Models

Our research objective is to disentangle the effects of loan officers from those of banks in the lending process. In this section, we outline the fixed effects methodology we employ.

We begin with a baseline model that regresses lending terms and loan performance on firm characteristics, loan terms (other than the dependent variable), borrower-industry fixed effects, and year fixed effects:

$$Y_{ibkt} = \beta_1 X_{jt} + \beta_2 Z_k + \delta_h + \mu_t + \epsilon_{ibkt}, \tag{1}$$

where i denotes loan officer, b denotes bank, j denotes the firm in which the loan officer lends to, k denotes the loan package, and t denotes time. In the above equation, Y_{ibkt} is either the lending term (*Spread*, *Covenants*, or *Maturity*) or loan performance (*Defaults*, *Downgrades*, or *ROA*) associated with loan officer i's loan to firm j at time t while employed by bank b. The variables X_{jt} and Z_k control for time-varying attributes of the borrower and loan contracts, as discussed in Section 2.3.3. The vector δ_h captures industry-fixed effects for which firm j is a member of. The vector μ_t controls for year fixed effects.

To estimate the explanatory power of individual loan officers and the banks that employ them, we next add loan officer- and bank-fixed effects ϕ_i and θ_b to Eq. 1:

$$Y_{ibkt} = \beta_1 X_{jt} + \beta_2 Z_k + \delta_h + \mu_t + \phi_i + \theta_b + \epsilon_{ibkt}, \tag{2}$$

Our objective in this analysis is to retrieve the loan officer- and bank-fixed effects ϕ_i and θ_b by exploiting variation in loan officers employed at the banks in our sample, and estimate their incremental explanatory power to the variables of interest.

In order to estimate loan officer fixed effects from Eq. 2, one needs to observe loan officer movement. As such, a loan officer must be observed in at least two banks in the sample, and a bank must employ at least two such loan officers. This empirical approach was originally presented in Bertrand and Schoar (2003) and has subsequently been referred to as the mover dummy variable approach (MDV). One concern with this approach is that it relies on a sample consisting of only movers, thus potentially limiting the external validity of the analysis. Accordingly, our main analysis relies on a modified version of the MDV approach introduced by Abowd, Kramarz, and Margolis (1999) and later refined by Abowd, Creecy, and Kramartz (2002), henceforth the AKM method.

The AKM method allows us to expand our analysis to both "movers" and "non-movers." With the AKM method, we are able to separate loan officer and bank fixed effects through a connectedness sample containing a set of banks connected through movers. To construct the connectedness sample, we track all the banks that loan officers in our sample are ever employed by, and consider a common loan officer as a "connection" between banks. Using these connections, we extract all the connected components as our sample of banks, thus requiring all banks to employ at least one loan officer that can be observed in another bank. This allows us to estimate loan officer and bank fixed effects within the connected set of banks following the procedures outlined in Cornelissen (2008) and more recently, Liu et al. (2016).

The following steps illustrate the AKM approach in more detail. We begin by modifying Eq. 2 to allow for the estimation of loan officer and bank effects through the connectedness sample as opposed to the "movers" only sample. As discussed above, this approach includes all loan officers and banks regardless of whether the loan officer transitions across banks. To illustrate, consider the dummy variable D_{ibt} which is equal to one if loan officer i works at bank b in year t and zero otherwise. Eq. 2 can be rewritten as follows:

$$Y_{ibkt} = \beta_1 X_{jt} + \beta_2 Z_k + \delta_h + \mu_t + \phi_i + \sum_{b=1}^{B} D_{ibt}\theta_b + \epsilon_{ibkt}, \tag{3}$$

where J indicates the collection of banks in our sample.

The AKM method first averages across all of loan officer i's lending terms or loan performance outcomes to obtain the following:

$$\bar{Y}_i = \beta_1 \bar{X}_i + \beta_2 \bar{Z}_i + \bar{\delta}_i + \phi_i + \sum_{b=1}^{B} \bar{D}_{ib}\theta_b + \bar{\mu}_t + \bar{\epsilon}_i, \tag{4}$$

Accordingly, Y_i is the average lending term or loan performance for a deal associated with a loan officer across the entire sample period. Next, Eq. 3 can be demeaned by Eq. 4:

$$(Y_{ibkt}-\bar{Y}_i) = \beta_1(X_{jt}-\bar{X}_i)+\beta_2(Z_t-\bar{Z}_i)+(\delta_h-\bar{\delta}_i)+\sum_{b=1}^{c}(D_{ibt}-\bar{D}_{ib})\theta_b+(\mu_t-\bar{\mu}_t)+(\epsilon_{ibkt}-\bar{\epsilon}_i), \tag{5}$$

The demeaning process removes the loan officer fixed effects (ϕ_i) from the estimation process. Accordingly, we are able to use movers' information to identify bank fixed effects since $D_{ibt} - \bar{D}_{ib} \neq 0$ for a mover. This can be estimated using the least square dummy variable approach following Andrews et al. (2006). We can then re-arrange the terms in Eq. 4 to obtain the following estimates of loan officer fixed effects:

$$\phi_i = \bar{Y}_i - \beta_1\bar{X}_i - \beta_2\bar{Z}_i - \bar{\delta}_i - \sum_{b=1}^{B}\bar{D}_{ib}\theta_b - \bar{\mu}_t \tag{6}$$

It is important to note that prior studies indicate that an estimation bias might result if our loan officer movement sample is small (Abowd et al. (2004), Andrews et al. (2006), Liu et al. (2016)). We do not expect this bias to be severe in our sample as we observe about 17% of loan officers move across banks in our connectedness sample. This number is similar to recent studies using the AKM procedure.[5]

In sum, we view both the AKM and MDV approaches as having trade-offs. The AKM method allows us to infer connections through the full sample of loan officer and bank pairs and thus is more generalizable.[6] However, this method also introduces potential biases if the sample of movers is small. On the other hand, the MDV approach focuses on only movers and reduces the potential for such biases to arise, but is limited in its external validity. Consistent with prior literature, we present the AKM method as our primary analysis, and demonstrate the robustness of our results using the mobility sample and the MDV approach.

[5] For example, Liu, Mao, and Tian (2016) report that 16% of inventors in their sample move, Ewens and Rhodes-Kropf (2015) report 30% of venture capital partners move in their sample, and Graham, Li, and Qiu (2012) report that only 5% of executives in their sample move.

[6] Note that prior studies also indicate that the AKM method has the added benefit of being more computationally feasible. However, we refrain from making this claim for our sample given the substantial increases in computing power in recent years. For example, Graham, Li, and Qiu (2012) claim that approximately 6GB of memory is needed to compute MDV fixed effects for a sample of 65,000 executives. This amount of memory is rather standard in current computer configurations.

3 Univariate Analyses

3.1 Loan Officer Descriptive Statistics

Table 1 describes the movement of loan officers in our sample. Panel A presents the frequency of loan officers moving within our sample. Our final sample consists of 7,892 loan officers, of which 1,325 move at least once during our sample. Thus, movers represent nearly 17% of our sample. This statistic is comparable to recent studies examining employment movement. For example, Graham et al. (2012) and Liu et al. (2016) find that movers account for approximately 5% and 16% of the population of employees examined, respectively. Panel B reports the number of banks with movers. Our sample consists of 982 banks, of which about 55% employ at least one mover during the sample period. Moreover, 42% of banks in our sample employ between one to five movers. As we examine higher thresholds on the number of moves per bank (e.g., 6–10, 11–20, etc.), we find that these banks constitute less of our sample. Consistent with prior studies, there is a negative relation between the number of banks and the number of movers they employ.

<u>Table 1 About Here</u>

Figure 1 reports the distribution of the titles for loan officers in our sample, as observed in the electronic signatures extracted from the SEC loan contracts. Roughly 60-70% of loan officers in our sample hold positions as senior vice presidents (Senior VP), vice presidents (VPs) or managing directors. About 10-15% of loan officers are bank CEOs and board directors. As our study focuses on mid-level managers, we conduct robustness analyses (untabulated) excluding these senior employees. All our results are both qualitatively and quantitatively similar when we exclude higher-level management from the sample.

Overall, the trends in Table 1 indicate that the labor market for loan officers appears to be quite dynamic. We document substantial variation in both the number of banks in which loan officers are employed as well as the number of moves each bank experiences. This variation suggests that we can exploit fixed effects models in separating the effects

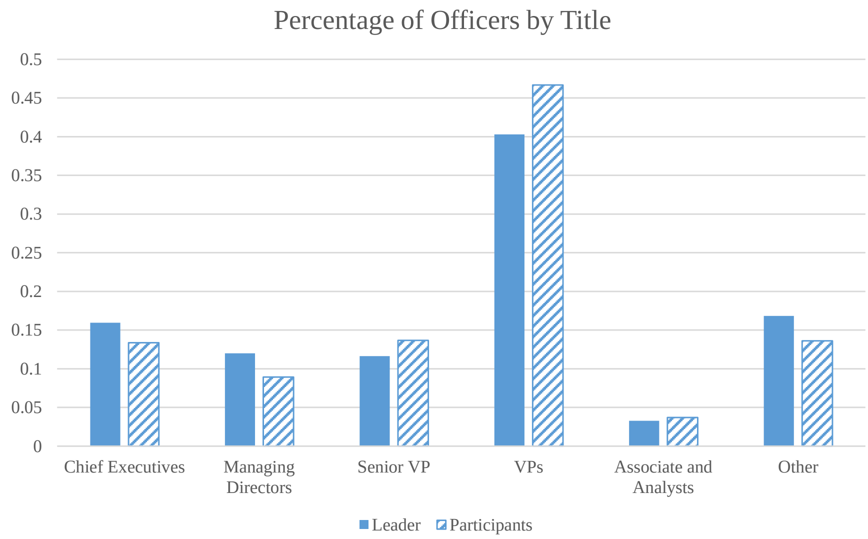


Figure 1. Distribution of loan officer titles
This figure describes the distribution of the titles of loan officers that issued syndicated loan contracts. The vertical axis represents the percentage of total loan officers. The horizontal axis displays titles in a bank. The solid columns indicate the percentage of officers with each title in a syndicated lead arranger bank. The patterned columns indicate the percentage of officers in a participant bank.

of loan officers and banks in lending decisions.

We further visualize the career movement of loan officers using a group of banks across which we observe at least 20 movers. Figure 2 describes the mapping among this set of banks. In this plot, the size of each node is proportional to the number of movers within each bank. The edges connecting the nodes represent the connections among banks that are formed by movers. Bank of America Merill Lynch, Wells Fargo, and JP Morgan are among the top in terms of officer movements. This is consistent with prior empirical evidence indicating that these banks also dominate the syndicated lending market in terms of market share (Ross (2010)).

We next inspect the number of loans issued by each loan officer as observed in our sample. This helps us better understand the data structure and validate the testing sample. Figure 3 counts the number of loans issued by each loan officer in our sample, and plots the percentage of loan officers observed issuing a given number of loans. Over 70% of loan officers in our sample issue fewer than three loans, and 44% of them issue only one loan.

With this data structure, we continue to examine whether loan officers in our sample specialize in extending credit to certain industries. Using the industry classification of

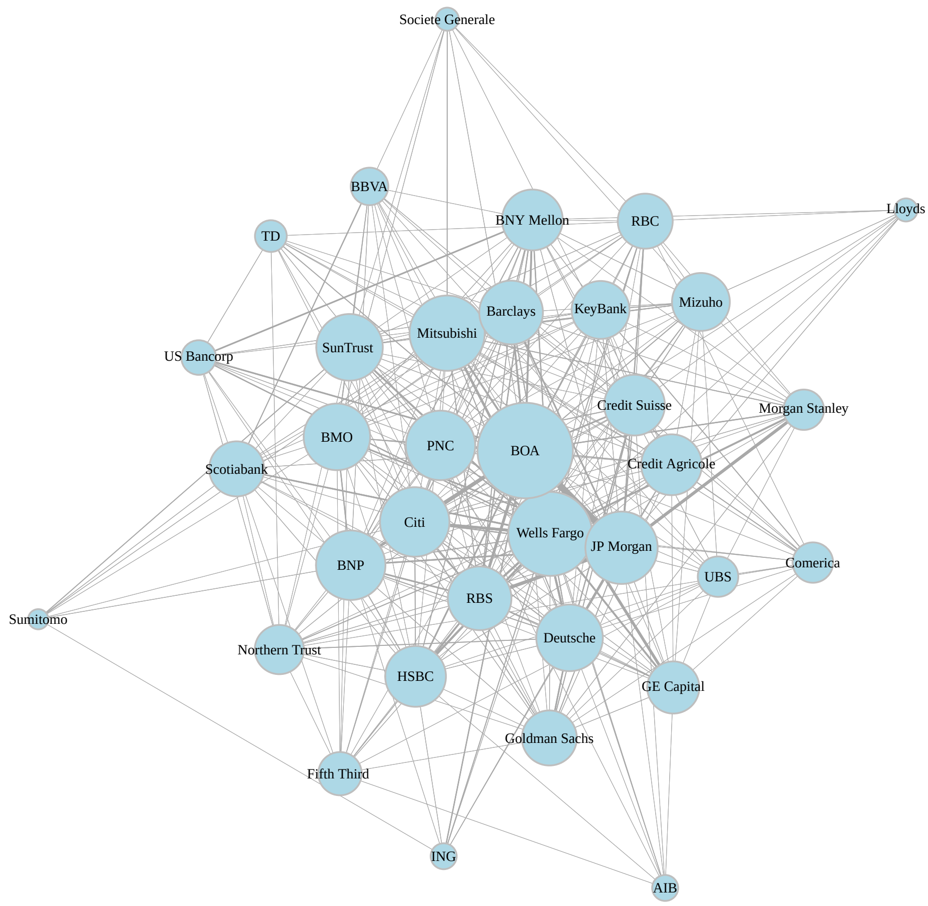


Figure 2. A network of banks connected by officer movement
This figure describes the connectedness among a set of banks that contain at least 20 movers (officers that can be observed in more than one banks). The size of the nodes reflects the number of movers within the sample of banks.

our sample borrowers, we count the number of industries covered by a given loan officer and plot the distribution of loan officers covering a certain number of industries. Figure 4 describes the industry concentration of loan officers. The majority of loan officers issue loans in only one industry, and nearly 90% of loan officers issue loans in only one or two industries.[7] This pattern suggests that the job function of loan officers is highly specialized.

Finally, we examine whether our sample fairly represents the Dealscan universe, as there is a high level of attrition when we match Dealscan data to SEC documents. Accordingly, Figure 5 compares the industry distribution of borrowers in the Dealscan universe to the industry distribution of borrowers in our sample. The figures suggest that the ma-

[7] As shown in Figure 3, single loan officers (i.e., loan officers issuing only one loan) represent 30 percent of our sample. Therefore, the observed industry concentration of loan officers are unlikely to be driven by officers with only one loan.

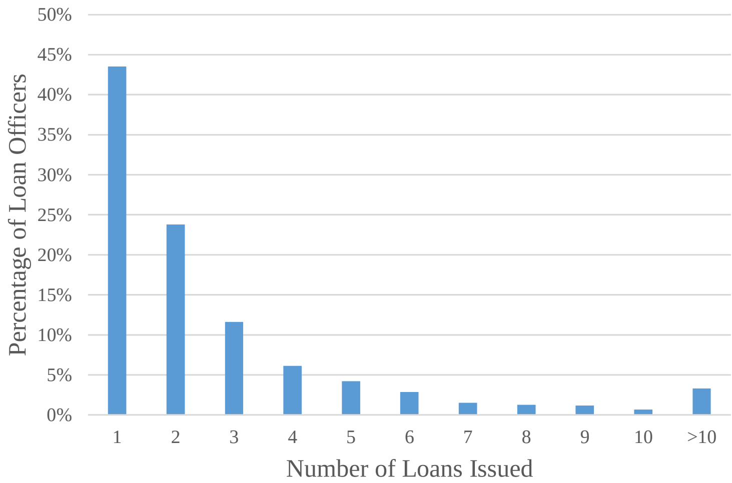


Figure 3. Number of loans issued by a loan officer
This figure describes the number of loans issued by a given loan officer. The horizontal axis shows the numebr of loans issued by a loan officer, and the vertical axis suggests the percentage of officers issuing the corresponding number of loans.

jority of borrowers in both samples are concentrated in manufacturing industries. The percentage of borrowers in other industries is also similar: Transportation & Communication, Services, Wholesale & Retail, and Mining industries constitute the majority of borrowers outside of manufacturing industries. Agricultural firms, on the other hand, constitute a very small portion of the sample. Overall, the visual inspection of industry composition suggests that the sample attrition does not affect the generalizabilty of our inferences to the entire Dealscan universe of borrowers.

3.2 Summary Statistics

Table 2 describes the summary statistics of our variables of interest. For each variable, we report the statistics from four samples. We start with the initial sample from Dealscan that we match to borrowers' SEC filings. This sample contains 41,977 loan contracts, 24,693 of which have complete information regarding loan contract terms and borrower characteristics. After matching the initial Dealscan sample with loan officer signature data from SEC documents, we are left with a sample of 15,513 loan contract-officer observations ("Full Sample") in which we observe all borrower characteristics. To conduct AKM analyses, we further restrict the full sample to the loan contracts extended by a group of banks that are connected by movers ("Connectedness Sample"). Finally,

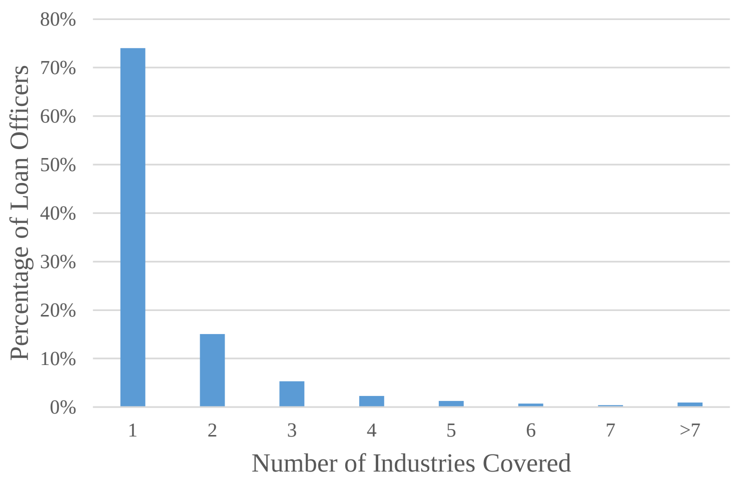
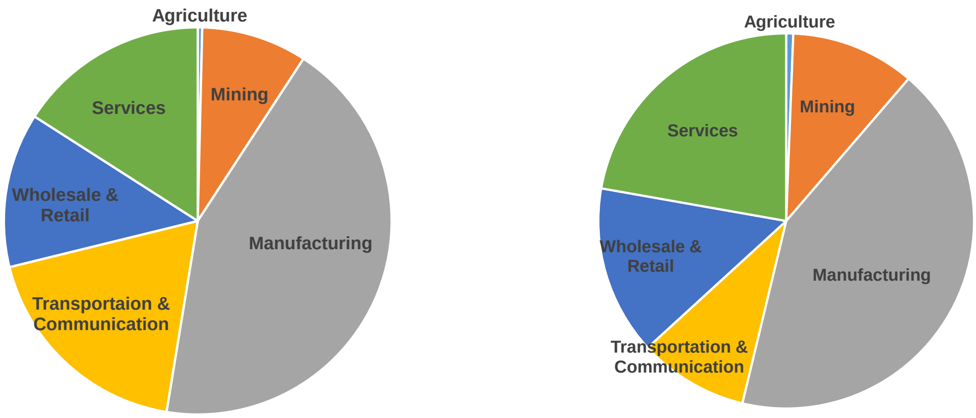


Figure 4. Industry coverage of loan officers
This figure describes the number of industries covered by a given loan officer inside a bank. Industry is defined by two-digit SIC industries. The horizontal axis indicates the number of industries covered by a loan officer, and the vertical axis suggests the percentage of officers covering the corresponding number of industries.



(a) Distribution of Borrower Industry in Dealscan **(b)** Distribution of Borrower Industry in Sample

Figure 5. Distribution of Borrower Industries. This figure presents the percentage of borrowers' industries in all Dealscan loans and in our sample. Panel (a) illustrates the percentage of Dealscan loans where the borrowers belong to a given industry. Panel (b) illustrates the percentage of loans in our sample where the borrowers belong to a given industry.

we consider the sample comprised of only loan contracts extended by movers, which constitute the basis for our MDV estimation ("Mobility Sample").

TABLE 2 ABOUT HERE

Panel A reports summary statistics for loan contract terms. The average loan contract in the connectedness sample has a slightly higher loan spread (194 basis points), more covenants (around 2 covenants), and a longer maturity (53 months) than the average contract in Dealscan, which specifies 186 basis points in loan spreads, 1.8 covenants, and 48 months in maturity. However, the differences in loan contract terms between these two samples are economically small. Loan contract terms also do not vary significantly between the connectedness sample and the mobility sample. The contract terms of loans in the mobility sample are very close to those in the initial Dealscan sample.

Panel B presents the summary statistics for loan performance measures. In general, the descriptive statistics appear to be in line with prior studies. For example, defaults are generally rare, accounting for only 4% to 6% of the sample. Downgrades also seem to be uncommon, as the average firm receives only a one-notch downgrade and the median firm receives no downgrade. Borrowers in our sample appear to be more profitable than typical borrowers, with an average level of *ROA* being around 1.2%, compared to the average *ROA* of 1.1% in the Dealscan sample. All of these statistics suggest that our sample of borrowers are on average financially healthy. Moreover, the average occurrences of *Default*, the extent of *Downgrades*, and the average level of *ROA* are comparable across the three samples.

Panel C describes the summary statistics of our firm-level control variables. Our sample firms are slightly larger than the average firm in Dealscan. They are also around two years older than the average Dealscan firm. The average level and the distribution of all other variables are similar across all samples, suggesting that it is unlikely that our sample selection introduces a strong bias.

4 Fixed Effects Regression Results

In this section, we present tests examining the relative explanatory powers of loan officer fixed effects and bank fixed effects. Our goal is to shed light on the influence of loan officers on setting lending terms and influencing loan performance.

Table 3 presents estimates of three-way-fixed-effect regressions where the outcome variable reflects lending terms (*Loan Spreads*, *Loan Covenants*, or *Loan Maturity*). Panel

A reports the incremental R^2s explained by officer fixed effects and bank fixed effects for loan contract terms when added to a baseline model (Equation 1). We report separately the explanatory powers of loan officers and banks for spreads, covenants, and maturity. For each loan contract term, we first present the R^2 of the baseline model (line (a), specified in Equation 1). We then add loan officer fixed effects (line (b)) and bank fixed effects (line (c)) separately into the baseline model and extract the incremental R^2s from each set of fixed effects. Finally, we add both loan officer fixed effects and bank fixed effects in the baseline model (line (d)), extracting the incremental R^2 of loan officer fixed effects in addition to bank fixed effects. Panel B reports the results from AKM estimation, as specified in Equation 2. In this panel, we report both the percentage of variations explained by officer effects and bank effects (R^2 explained) as well as the joint significance of these effects (F-test on FE). Column (1) reports results for *Loan Spreads*, Column (2) reports the estimation results for *Loan Covenants*, and Column (3) presents results for *Loan Maturity.* In Panel B, we report both the R^2 explained by officer and bank fixed effects as well as the joint F-test significance of each set of fixed effects.

Table 3 About Here

Across all three lending terms, loan officer fixed effects explain a substantial portion of the variation in lending terms. For example, the first section of Panel A shows that the baseline model for loan spreads yields an R^2 of 52%, suggesting that borrower and loan characteristics combined explain a little more than half of the total variation in the pricing of corporate loans. Adding loan officer fixed effects increases the R^2 to 75.8%, an increase of roughly 24%. In contrast, adding bank fixed effects only improves the R^2 by 9.3%, less than half of the increase brought by loan officer effects. Column (1) of Panel B shows that, in a relative sense, loan officer fixed effects explain 4.5 times more variation in loan spreads than do bank fixed effects. Loan officers explain a large portion of the variation in non-pricing contract terms as well. Our estimates in Panel A suggest that loan officers explain 37% of the variation in loan covenants and 26% of the variation in maturity, while bank fixed effects explain a much smaller portion (7.8%

in loan covenants and 6.9% in maturity). Based on the AKM estimation, loan officers explain up to five times more variation in loan covenants (Column (2) of Panel B) and nine times more variation in maturity (Column (3)) than do banks. These tests include a wide array of controls for firm characteristics and lending terms, as well as fixed effects for loan type, borrower-industry, and year. In sum, we find strong evidence to suggest that loan officers exert significant influence in setting lending terms, particularly for loan covenants. Moreover, loan officer effects appear to be more economically important than bank effects in explaining the heterogeneity in lending terms.

Having established robust evidence that loan officers have a significant impact on lending terms, we next examine whether loan officers affect ex post loan performance. If delegated with powers to screen and monitor the borrowers, loan officer effects should exhibit pronounced explanatory powers not only in the ex ante negotiated lending terms, but also in ex post loan performance.

Table 4 reports the explanatory powers of loan officers and banks for loan performance (*Defaults*, *Downgrades*, or *ROA*). Panel A reports the incremental R^2s estimated from traditional fixed effect models. From the baseline specifications, borrower characteristics, loan contract features, industry classification, and time-specific conditions generate R^2s of 24% for loan defaults, 29% for downgrades, and 40% for borrower ROA. When we include loan officer fixed effects in these regressions, we observe the R^2s increase by over twofold, reaching 71% for loan defaults, 68% for downgrades, and 74% for borrower ROA. Hence, loan officer effects explain as much or even more of the variation in loan performance as those well-known borrower and loan characteristics. In stark contrast, bank fixed effects contribute to less than 10% increases in R^2 across all performance measures.

Panel B reports the explanatory powers of loan officer and bank effects from AKM estimation. Column (1) examines our primary measure of performance, *Defaults*, while Columns (2) and (3) examine alternative measures of performance (i.e., *Downgrades* and *ROA*). Across all three measures, loan officers exhibit a significant impact on loan performance, especially when performance is measured by *Default* (with R^2 reaching 53%). In a relative sense, loan officers explain fourteen times as much variation in loan default than do bank fixed effects. Compared to banks, loan officers seem to be more influential when performance is measured based on *Downgrades*, with officer fixed effects explaining up to 63 times more variation than do bank fixed effects.

<ins>Table 4 About Here</ins>

Overall, results from our baseline estimation suggest that loan officers play an important role in setting loan terms and exert significant influence on loan performance. These findings indicate that banks delegate substantial decision rights to loan officers in extending credit to corporations. In the next section, we conduct a battery of robustness tests that help to alleviate endogeneity concerns associated with our empirical methods.

5 Analysis of Endogeneity Concerns

As discussed above, the analyses in this study are estimated using the AKM method. This methodology estimates bank effects using the difference in outcome variables (i.e., lending terms or loan performance) associated with loan officers' moves across banks (see Eq. 5), and then backs out loan officer fixed effects by comparing outcomes of loan officers within a given bank (see Eq. 6). Although this method generally provides consistent estimates of loan officer and bank fixed effects, it could potentially introduce biases when the sample lacks sufficient career movements of loan officers, or when such movements are correlated with unobservable, time-varying features of the bank or the loan officer. In this section, we provide an extensive discussion on specific empirical challenges this method faces. We then validate our base results through an array of tests designed to address each of these challenges.

5.1 MDV Method

Given that our primary testing method relies on loan officers' career information to identify bank effects, the empirical power of our tests depends crucially on the number of career movements in the sample. If there is limited movement in our sample, the estimated fixed effects could be fraught with errors and even over-estimate the explanatory power of loan officer fixed effects (Graham et al. (2012)). Our baseline sample consists of 891 movers and 4,403 non-movers, thus indicating that 17% of the loan officers in our sample move across banks. As discussed earlier, we believe this is a reasonable level of movement that is in line with prior studies (e.g., Graham et al. (2012); Ewens and Rhodes-Kropf (2015)). Nevertheless, we still test the sensitivity of our results to a sample that is restricted to only movers.

Specifically, we consider a subsample of loans extended only by movers, i.e., officers that can be observed in at least two banks during our sample period. Within this sample, we directly estimate the incremental R^2 contributed by movers and the banks they have worked in. This method regresses our variables of interest (i.e., lending terms and loan peformance) on dummy variables defined for only movers and their banks (i.e., mover-dummy-variable method, or MDV method). As the MDV method employs a sample of 100% movers, it alleviates the concern that insufficient testing power resulting from a lack of career movement biases our inferences. This methodology is similar to that used in Bertrand and Schoar (2003). It is important to note, however, that this approach draws inferences from a restricted sample that focuses only on movers, and thus may be limited in its generalizability.

Table 5 presents the results from estimating Equation 2 using the MDV method. In Panel A, we present the results for lending terms (*Loan Spreads*, *Loan Covenants*, and *Loan Maturity*). In Panel B, we present the results for loan performance (*Default*, *Downgrades*, and *ROA*). For each variable we present four rows of results. First, we present the explained R^2 based on a baseline regression of the outcome variable on control variables. We then independently augment the baseline model with loan officer fixed effects and bank fixed effects, and display the F-statistics, total explained R^2 and incremental R^2 explained for each set of fixed effects. Finally, we present statistics after including both loan officer and bank fixed effects. The mobility sample admits only 6,172 observations, a reduction of approximately 60% from the baseline analyses.

<u>TABLE 5 ABOUT HERE</u>

The results from the MDV approach continue to suggest that loan officers play a significant role in setting lending terms and influencing loan performance. In Panel A, including bank fixed effects increases the R^2s from regressions of *Loan Spreads*, *Loan Covenants*, and *Loan Maturity* by 9%, 11%, and 8%, respectively. Adding loan officer fixed effects in these regressions increases the R^2 by 16%, 23%, and 16%, respectively. Panel B reports similar results for loan performance. Across all three measures of performance, we find that regressions of performance on loan officer fixed effects generates higher explanatory power in terms of incremental R^2 than do regressions of performance on bank fixed effects alone. Adding loan officer fixed effects increases the R^2 from regressions of *ROA*, *Default* and *Downgrades* by 25%, 23%, and 18%, respectively. Consistent across all of the dependent variables, the incremental R^2s generated by loan officer effects are about twice as large as those generated by bank fixed effects. Overall, the results based on the MDV approach suggest that loan officer fixed effects continue to explain a significant portion of the variation in lending terms and loan performance, even within this limited mobility sample.

5.2 Assortative Matching Between Loan Officers and Banks

Studies using labor market data often face the challenge of assortative matching between employees and institutions. Assortative matching reflects the possibility that high (low) quality firms are often able to hire high (low) quality employees, or that people working in certain institutions tend to have similar risk preferences, judgment, or disposition (Becker (1973, 1974)). Within the context of our study, assortative matching between loan officers and banks may manifest in banks with low risk tolerance being more likely to hire conservative officers, and vice versa. These matching outcomes may generate an array of interesting and nuanced implications for our inferences. In this section, we discuss each of these implications in turn.

First, we consider the scenario of stationary assortative matching. In this scenario, movement across banks is driven by loan officers seeking positions in banks that have similar time-invariant characteristics that are potentially relevant to lending decisions (e.g., risk tolerance). Under such circumstances, the changes in a mover's lending decisions from the previous, ill-fitted bank to the new, well-fitted bank would be attributed to differences between fixed effects from those two banks. In other words, regardless of whether differences in lending outcomes arise from changes in loan officer behavior (individual effect) or changes in bank environment (bank effect), those differences are completely attributed to the bank by the AKM method (Ewens and Rhdoes-Kropf 2015). For example, if a loan officer is fired and moves to a worse bank, and this subsequently affects her performance, the AKM method would attribute the decline in performance to bank fixed effects. A similar situation arises if a loan officer is a high-quality employee that seeks better jobs at more prestigious banks, which then improves her performance. Again, the AKM method would attribute all such changes in performance to the differences in banks, instead of the loan officer. Overall, the above discussion suggests that stationary assortative matching would underestimate loan officer fixed effects and bias against finding our results that loan officers impact the lending process.

We next consider a more complicated form of assortative matching in which loan officers or banks have time-varying preferences or characteristics. We consider two scenarios related to forms of "dynamic" matching. First, movers' lending decisions may be based on their anticipation of changes in their own behavior in the future. As such, loan officers may move to banks that better suit their future contracting tendencies. Second, it is also possible that movers in our sample differ from non-movers in that they want to benefit from better interactions with future colleagues. In either case, the AKM method attributes changes in lending outcomes to bank fixed effects, resulting in an overstatement of bank fixed effects. As is the case with stationary matching, dynamic matching between loan officers and banks will also bias against us finding that loan officers impact the lending process.

The above discussion examines situations in which assortative matching would bias against our findings. We next discuss scenarios and empirical strategies for types of assortative matching that pose concerns for our inferences. We begin by visually inspecting the severity of matching effects between loan officers and banks in our sample. To do so, we compute the variation in loan contract terms extended by all officers in a given bank at a given time, and compare that with the variation in loan contract terms extended by a randomly-selected, equal-sized group of loan officers in the same year. For example, if our sample includes 40 loan officers working in Citibank during 2003, we will randomly sample 40 loan officers in 2003 and compare the standard deviation of the loan contract terms they issue with the standard deviation of loan contract terms issued by the 40 loan officers employed by Citibank.

Figure 6 displays results from this simulation. For brevity, we display the three lending terms and only our primary performance measure, although we note that results based on alternative loan performance measures yield similar inferences. Across all of the outcome variables, the graphical evidence suggests that matching is not particularly pronounced in our sample. For some group sizes and loan terms (e.g., *Loan Spreads* for groups 15 and 16), the average standard deviation of loan contract terms issued by officers employed by the same banks are almost indistinguishable from the average standard deviation of loan contract terms issued by a random sample of loan officers. Although being far from conclusive evidence regarding the degree of matching problems in our sample, the graphical evidence does provide some visual support to indicate that matching is not overly pronounced.

Having provided visual evidence on the severity of matching, we next discuss scenarios that will lead us to bias against finding bank effects, and would thus result in an over-estimatation of loan officers' importance. One such scenario is when a bank decides to change its lending policies and hires loan officers suitable for this new direction. The newly-hired loan officers may move from a bank with policies similar to the bank of interest adopting the new policies, thus resulting in a small observed difference between her lending terms before and after her move. Given that our empirical method takes into ac-

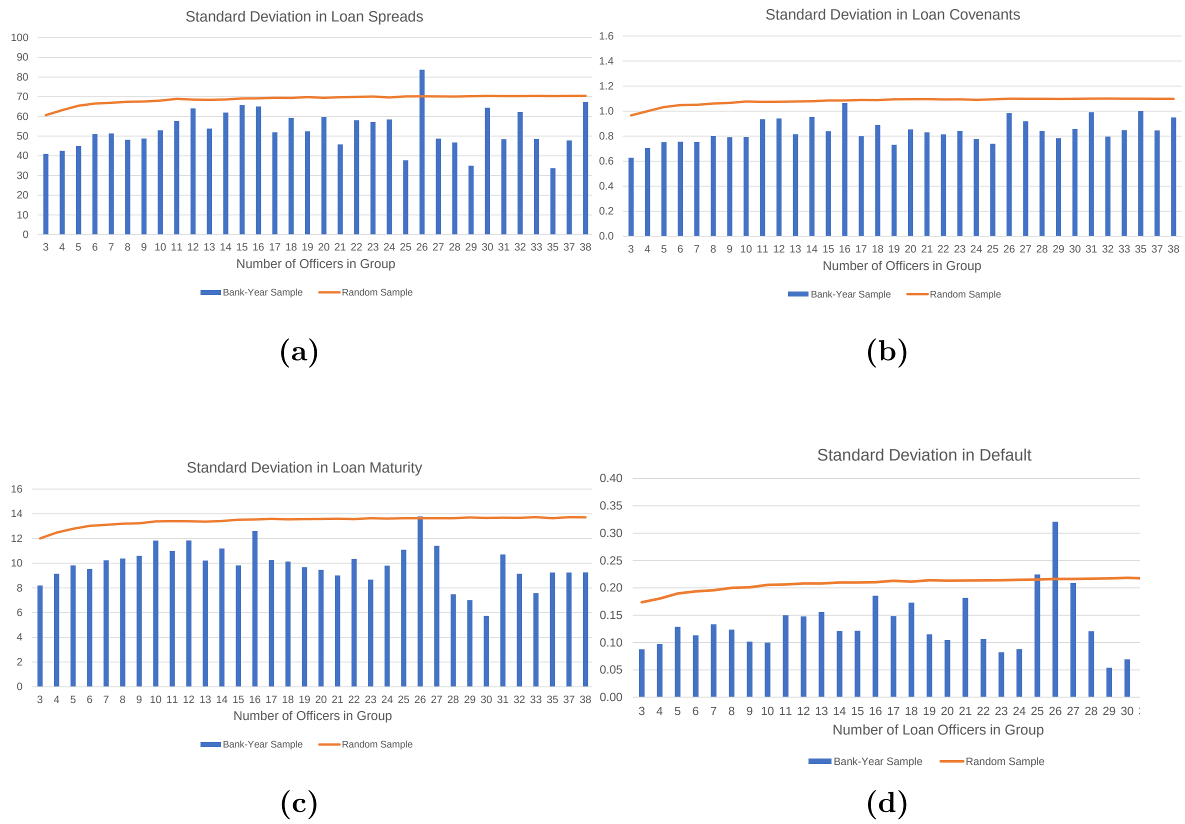


Figure 6. Scramble test of the variation in lending decisions. This figure presents the standard deviation of bank loan contract terms and performance for loan officer fixed effects in a given bank-year in our sample, compared with a randomly selected sample of loan officer fixed effects of equal group size. Panel (a) presents the standard deviation for loan spreads; Panel (b) presents the standard deviation for loan covenants; Panel (c) presents the standard deviation for loan maturity; and Panel (d) presents the standard deviation of loan default. In each panel, the columns suggest the standard deviation of loan officer fixed effects from actual bank-year groups. The solid line indicates the standard deviation from randomly selected samples of the same size. The horizontal axis indicates the number of loan officers in a given bank-year. The vertical axis indicates the standard deviation.

count such a difference when estimating bank-fixed effects, it may underestimate changes in bank-level policies. To address this possibility, we augment our baseline analyses with bank-year two-way interacted fixed effects. These fixed effects control for time-varying bank characteristics such as performance, risk preference, or policy choices. To our knowledge, this test also represents an extension of the prior literature as other studies lack sufficient variation in the labor pool to include time-varying institutional fixed effects in their analyses.

Table 6 reports results from estimations of the AKM method after including 1,977 bank-year two-way interacted fixed effects. While economically more modest, the results continue to indicate that loan officers explain a large portion of the variation in lending terms and loan performance. Depending on the specific outcome variable we examine, loan officer fixed effects explain around three times more variation than bank-year fixed effects. Overall, this analysis suggests that, even after controlling for banks' time-varying preferences, loan officers play an important role in influencing lending terms and loan performance.

TABLE 6 ABOUT HERE

Along similar lines, potential biases could also arise when loan officers move between similar banks. If loan officers move between banks with similar lending policies or risk preferences, the AKM method would estimate a small difference in lending outcomes, thus contributing to a small estimated bank fixed effect. If the career movements in our sample predominantly occur between similar banks and there are few movements between banks with drastically different lending policies, we would mistakenly attribute the small differences in loan contract terms across banks as being representative of the universe of syndicated lenders. In this scenario, bank fixed effects will be under-estimated in the lending terms and performance regressions.

To examine the robustness of our results to this concern, we restrict our sample to a mapping of banks connected by loan officers who move between differently-ranked banks. Specifically, we consider two types of movers, movers-up and movers-down. We define a loan officer to be moving up if her previous employment was at a bank that was not ranked in the top 20 in terms of market share, but is currently employed by a top-20 bank. Analogously, we define a loan officer to be moving down if she transitions from a top-20 bank to a non-top-20 bank. We examine the sample of loans extended by a network of banks that are connected only by movers-up and movers-down. In such a subsample, we effectively remove loan officers that move between similar banks from our sample. In other words, this subsample "biases" our estimation towards finding stronger bank effects.

Table 7 presents the results from this analysis. The sample contains 7,284 observations, indicating that a large portion of our original sample of loan officers moves to a distinctly different institution. Using this restricted sample, we continue to find that loan officers have a significant impact on lending terms and loan performance. Depending on the variable of interest, loan officer fixed effects explain 6 to 13 times more variation in R^2 than do bank fixed effects. Overall, this analysis suggests that our baseline findings are unlikely to be explained by loan officer movements between similar institutions.

Table 7 About Here

5.3 Matching Between Loan Officers and Firms

The above discussion focuses on whether and how the matching between loan officers and banks can bias our inferences. In our last set of analyses regarding endogeneity concerns, we discuss whether the matching (or selection, or assignment) of borrowers to loan officers can confound our analyses. From the prior literature, it is unclear how borrowers are chosen in lending markets. For example, Hertzberg et al. (2010) study a market segment where banks assign borrowers' loan applications to officers, thus giving officers no influence in the initial selection of borrowers. Other studies conduct experiments in which officers are incentivized to seek potential borrowers (Agarwal and Ben-David (2014)). It is not clear which approach is adopted by the majority of U.S. corporate lenders. Below, we discuss the implications for our findings if banks play a dominating role in the allocation of borrowers to loan officers.

In the extreme scenario, where all borrowers are assortatively matched with banks, loan officers do not play any role in prospecting or screening borrowers. This scenario would lead our econometric methods to (correctly) attribute the differences in borrowers' performance to bank-level differences. It is thus unlikely that our econometric method will bias the estimation of bank-fixed effects downwards due to banks' selection of borrowers.

Nonetheless, we augment our baseline analyses with bank-borrower two-way fixed effects and re-examine our main analyses. These tests artificially attribute all the decision rights related to borrower selection to banks. Conceptually, although we do not rule out the role of loan officers in selecting and screening borrowers from our framework, these tests provide an opportunity to examine loan officers' influence after requiring the bank to have an established lending relationship with the firm of interest.

Table 8 reports the results from this test. The number of observations in this test is reduced to 5,916 since estimation of bank-borrower fixed effects requires borrowers to have at least two loans with a bank. It is interesting to note that the number of loan officer fixed effects in this analysis (1,789 + 655 = 2,444) is similar in magnitude to the number of bank-firm fixed effects (2,387 pairs). Given the small sample size and the large number of fixed effects, this test is very restrictive. Nevertheless, we still find that loan officers are instrumental in setting lending terms and influencing loan performance. The relative explanatory power of loan officers to that of bank-borrower pairings remains larger than one in almost all of the outcome variables we examine. Facing a pre-selected borrower base in a given bank, loan officers still explain 30% (55%) of the decisions on the costs (maturity) of the loan contract, a figure that is around 26% (63%) higher than the explanatory power of the bank-borrower pair. Admittedly, loan officers seem to have weaker effects on setting the covenants on the loan contracts of a given borrower. To wit, the relative R^2 explained by loan officers over that explained by bank-borrower pairs is generally smaller than the relative R^2 in the main results. This is because we non-indiscriminately attribute all the variation in borrower characteristics to bank-level differences.

<u>TABLE 8 ABOUT HERE</u>

Before concluding our discussion on endogeneity, we offer one final comment on the issues related to endogenous matching. Despite our attempts to address endogeneity concerns, we admit that our empirical endeavor cannot fully address the complex effects that arise in labor market matching settings. As discussed by both Graham et al. (2012) and Ewens and Rhodes-Kropf (2015), the matching issue is present in any employer-employee matched dataset and is not unique to our methodology. Notably, compared to the previous studies, our study takes one step further in addressing this issue by controlling for observable and unobservable time-variant employer effects through the inclusion of bank-year two-way interacted fixed effects. This alleviates to a large extent the endogeneity issues resulting from time-varying employer characteristics.

6 Cross-Sectional Analyses

Having established that loan officers are instrumental in setting lending terms and influencing loan performance, we further explore how these influences vary across banks and over time. We also explore the heterogeneity in loan officers' fixed effects to better understand their influence.

6.1 Loan Officer Influence in Different Banks

We begin by examining how differences in bank characteristics are related to different degrees of delegation of lending decisions. We posit that large, complex banks might benefit more from higher levels of delegation as information asymmetries are more pronounced within these organizations. Accordingly, we partition our sample based on bank size and industry diversity, and re-examine the relative importance of loan officer fixed effects to bank fixed effects in each of those subsamples.

Table 9 provides the results from this analysis. Panel A provides results when the outcome variable is *Loan Spreads*. Panel B reports the results for *Loan Covenants*. Panel C reports results for *Loan Maturity*. Finally, Panel D presents the results for our primary loan performance measure, *Defaults*. In each panel, we partition banks by both their market shares in terms of newly issued loans, and the industry concentration of the loans they issue each year. Column (1) examine the subset of banks that issue more than 1% of loans in the syndicated lending market in a given year; Column (2) examine banks with less than 1% market share. Column (3) focuses on banks that issue loans to a diverse set of industries each year (below median HHIs in borrowers' industries), and Column (4) focuses on banks that issue loans to a concentrated set of industries (above median HHIs in borrowers' industries).

Table 9 About Here

The results from this analysis indicate that loan officers exhibit stronger influences over lending decisions and loan outcomes in large, diverse banks. For example, loan officer fixed effects explain around six times more variation in loan spreads than do bank fixed effects in large banks and 35 times more variation in loans spreads than do bank fixed effects in banks with diverse industry coverage. In contrast, loan officer fixed effects only explain three times more variation in loan spreads than do bank fixed effects in small banks and banks with concentrated industry coverage. The results depict a similar message as we examine other outcome variables with only one exception: Loan officer fixed effects explain less variation in covenants than do bank fixed effects in large banks than they do in small banks. Overall, these cross-sectional analyses generally indicate that loan officers are delegated more decision rights in complex organizations, potentially due to the increased costs of communication and heightened information asymmetries within these organizations.

6.2 Loan Officers' Effects Over Time

We next examine how loan officers' influence in the lending process has evolved over time. Prior studies argue that technological improvements have led to more efficient and automated lending processes (Petersen and Rajan (2002); Berger et al. (2005)). Thus, it is possible that loan officers are no longer important in the lending process in recent years and that their value has declined over time.

We test this conjecture by partitioning our sample into four time periods. In doing so, we try to maintain similar sample sizes across these subsamples. Given that our sample is more sparse in the 1990s and early 2000s, we split our sample period in half and consider 1994–2003 to be our first sub-period. In the rest of the sample period, we equally divide the nine years into three sub-periods. Specifically, we define the pre-crises years, 2004–2006, as our second sub-period, the crises years, 2007–2009, as our third sub-period, and the post-crises years, 2010–2012, as our last sub-period.

In our analyses across these sub-periods, we note that the proportions of movers over the total number of loan officers are significantly lower in each subsample relative to the main sample, and using the AKM method in those subsamples may induce biases. We thus extract the incremental R^2 from loan officer fixed effects and bank fixed effects from a simple fixed-effect model, without relying on the AKM method. Table 10 provides the results. Loan officers appear to play an important role in influencing lending terms and loan performance across all sub-periods. In the pre-crises years, loan officers exhibit a more pronounced influence over loan spreads and loan performance. However, in terms of other contract terms such as loan covenants and loan maturity, the effects of loan officers have remained steady in recent years. Comparing the first half of our sample period (1994–2003) and the later years of our sample, loan officers have exhibited a declining influence over these non-pricing terms. Overall, these tests suggest technological advancements have not reduced loan officers' influence on setting lending terms and influencing loan performance.

Table 10 About Here

6.3 Heterogeneity within Loan Officers

Our final analyses are exploratory and examine loan officer heterogeneity within banks. To this end, we conduct two sets of analyses. First, we examine correlations between loan officer fixed effects observed across different lending terms and loan performance to determine if there are any overarching patterns in loan officers' lending decisions. Second, we examine whether observable characteristics of loan officers (e.g., educational background, gender, and work history) explain patterns in lending decisions.

We start by investigating the inter-relation among loan officers' lending patterns. To conduct this analysis, we first extract loan officer fixed effects using the baseline AKM method. We then present simple correlations between the extracted loan officer fixed effects for each outcome variable.

Table 11 About Here

Table 11 reports the correlation of loan officer fixed effects across different lending outcomes. The results indicate a number of interesting patterns. First, loan officers that tend to issue higher spreads also tend to impose more covenants and lower maturity on the loan contracts. This pattern seems to suggest that delegation leads loan officers to develop distinct lending styles. Loan officers' lending terms (i.e., *Loan Spreads*, *Loan Covenants*, and *Loan Maturity*) are also correlated with their influence on loan performance (*Default*). For example, officer fixed effects on loan spreads and loan covenants are positively correlated with the occurrence of loan default rates. This suggests that officers who tend to issue loans with higher spreads and more covenants also grant riskier loans, i.e., lend to borrowers that are more likely to default. Moreover, loan officers that issue shorter maturity loans are also likely to issue riskier loans, as indicated by the negative correlation between loan officer fixed effects for *Loan Maturity* and *Default*. Taken together, these results suggest that loan officers recognize a borrower's riskiness. Consequently, they increase the markup on those loans and intensify their monitoring efforts on those borrowers accordingly.

Given the observed heterogeneity in lending styles, we further explore whether observable, time-invariant characteristics of loan officers contribute to the differences in their lending styles. To do so, we regress the estimated fixed effects of loan officers on loan contract terms and loan performance on the background characteristics of those loan officers obtained from their *LinkedIn* profiles. In this analysis, we consider five characteristics. The first characteristic we consider is *First Bank Size* which is the market share of the first syndicated lender that an officer works at after completing her education. Recent research indicates that an individual's early work experience shapes her judgment for the remainder of her career (e.g., He, Kothari, Xiao and Zuo (2016)). Next, we examine whether the education a loan officer receives helps shape her lending decisions. We thus define an indicator variable *Business/Econ Degree* that equals one if a loan officer majors in business degrees or economics in her undergraduate degree, and zero otherwise. We further consider an indicator variable *Top School* that equals one if a loan officer attended a top ten undergraduate or MBA program prior to joining our sample, and zero otherwise. Finally, we consider the gender and age of a loan officer, defining *Female* to indicate a female loan officer, and *Cohort Year* as the year that the loan officer entered college.

We regress the loan officer fixed effects estimated from our full-fledged fixed effect models (Equation 2) on the variables indicating their time-invariant background characteristics. Each unit of observation is a unique loan officer, who has available estimated fixed effects from the baseline tests and a complete *LinkedIn* Profile. Since we are only able to obtain *LinkedIn* data for a small subset of the loan officer population, the sample size in these tests is reduced to 919 unique loan officers. Table 12 presents the results from regressing officer fixed effects on each of their characteristics separately and jointly.

TABLE 12 ABOUT HERE

There are several interesting findings from our investigation. First, we note that many common and unobservable characteristics of the labor force are unable to explain loan officers' lending styles, as evidenced by the low R^2s ranging from 0.5% to 1.5%. However, the size of the first bank that a loan officer is employed at has a significant influence over the contract terms she extends later in her career. In univariate tests, *First Bank Size* is positively associated with the interest rate markups and loan covenants imposed by a loan officer. It is also negatively related to the maturity of the loan she grants. Finally, the size of a loan officer's first employer is also positively correlated with the level of loan risks, as *First Bank Size* is positively associated with *Default*. Note that the effects from these regressions are incremental to controlling for all observable firm characteristics, loan contract terms, bank effects, and time fixed effects.

Taken together, the results from our exploratory analyses suggest that loan officers that start their careers at large, prestigious institutions may develop a pattern of charging higher interest rates, imposing more covenants and extending shorter-term loans. However, the loans they originate have excessively high default rates. In addition, loan officers that graduate from top schools have a tendency of charging higher interest rates.

7 Conclusion

Despite being key economic agents and having the potential to influence billions of dollars in corporate lending each year, the role of loan officers has remained largely unexplored, especially in the U.S. corporate loan market. In this study, we seek to address this important question. We construct a comprehensive database that allows us to track the employment history, performance, and lending terms related to over 7,000 loan officers employed by major U.S. corporate lending departments from the period spanning 1994 to 2012. Our findings indicate that loan officers play an important role in both setting lending terms and influencing loan performance. These results are robust to a battery of endogeneity tests designed to address matching concerns that arise in the labor market of loan officers as well as the market for corporate lending.

Our study contributes to the literature by providing the first large sample evidence of the role of time-invariant loan officer heterogeneity in the corporate lending process. While a a growing literature has examined the role of loan officers in the lending process, these studies have mostly focused on foreign lending markets or case analyses of single banks (e.g., Liberti and Mian (2009); Berg, Puri, and Rocholl (2013), Mosk (2014), Drexler and Schoar (2014), Degryse et al. (2014), Agarwal and Ben-David (2014), Cole (2015)). By constructing a novel broad sample of major U.S. banks over time with loan officer identities matched to each lending agreement, we are able to examine and quantify the importance of loan officers in the corporate lending market and its dynamic changes in recent years. These findings should be of interest to researchers, regulators, and corporate borrowers.

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Appendix A Variable definitions

Size: Log of total assets (AT)

Age: Years after a firm's first appearance in Compustat database

Profitability: Operating income (OIBDP)/total assets

Tangibility: Property, plant, and equipment (PPENT)/total assets

M/B: (Stock price (PRCC)×shares outstanding (CSHO) + total assets – book equity (CEQ))/total assets

Leverage: (Long-term debt (DLTT) + current debt (DLC))/total assets

Ratings: A dummy variable that equals one if the firm has a bond rating, zero otherwise

Credit spread: Yield spread between average AAA-rated corporate bonds and average BBB-rated corporate bonds

Federal fund rate: Federal fund rate

GDP growth: Quarterly average of GDP growth rate of the year

Loan spread: All-in-drawn loan spread over LIBOR

Loan covenants: Total number of covenants on the loan package

Loan maturity: Loan maturity in months

Loan size: Log of total loan amount (in dollars)

Loan type: Indicators for whether a loan is a term loan, revolver, or other

Table 1
Loan officer and bank movement
This table shows the summary statistics for loan, borrower, officer, and bank characteristics, as well as macroeconomic variables. The sample spans over the period of 1994–2012, including all syndicated loans in Dealscan that we can identify loan officer signatures from the borrower's SEC documents. Panel A reports the statistics for our full loan contract-officer sample. Panel B reports the statistics for the sample of banks connected by movers used in AKM method. All continuous variables except *Leverage* are winsorized within 1 and 99 percentile. *Leverage* is restricted to the 0–1 range.

Panel A: Number of loan officers moving

Mover	No. of banks in which loan officers are employed	No. of Loan Officers	Percentage of total loan officers
No	1	6,567	83.21%
	Subtotal		
Yes	2	1,000	12.67%
	3	239	3.03%
	4	60	0.76%
	5	17	0.22%
	>5	9	0.11%
	Subtotal	1,325	16.79%
	Total	7,892	

Panel B: Number of banks with movers

Movers per bank	Frequency	Percentage of banks	Cumulative percentage
0	446	45.42%	45.42%
1–5	416	42.36%	87.78%
6–10	49	4.99%	92.77%
11–20	33	3.36%	96.13%
21–30	16	1.63%	97.76%
31–50	13	1.32%	99.08%
>50	9	0.92%	100.00%
Total	982	100%	

Table 2
Summary statistics
This table shows the summary statistics for performance measures, as well as loan and borrower characteristics. The sample spans over the period of 1994–2012, including all syndicated loans in Dealscan that we can identify loan officer signatures from the borrower's SEC documents. We compute summary statistics for the initial sample from Dealscan (before matching to signatures from SEC), the full sample of loans with signatures, the sample of loans with connected banks (*Connectedness* sample), and the sample with only movers (*Mobility* sample). Panel A reports the summary statistics for loan contract terms. Panel B reports the summary statistics for loan performance measures. Panel C reports the statistics for borrower characteristics. All continuous variables except *Leverage* are winsorized within 1 and 99 percentile. *Leverage* is restricted to the 0–1 range.

Panel A: Summary statistics of loan characteristics variables

Variable	N	Mean	Std. Dev.	25^{th} pctile	Median	75^{th} pctile
Loan Spreads						
Dealscan Sample	24,693	185.5925	133.8348	75	175	250
Full Sample	15,513	194.4486	137.7318	100	175	250
Connectedness Sample	14,715	190.1663	129.8214	100	175	250
Mobility Sample	6,172	187.4251	129.4239	87.5	175	250
Loan Covenants						
Dealscan Sample	24,693	1.7769	1.6161	0	2	3
Full Sample	15,513	1.9840	1.2958	1	2	3
Connectedness Sample	14,715	1.9671	1.2809	1	2	3
Mobility Sample	6,172	1.8715	1.2060	1	2	3
Loan Maturity						
Dealscan Sample	24,693	47.6045	23.9846	33	56	60
Full Sample	15,513	52.7827	19.2663	46	60	60
Connectedness Sample	14,715	52.8143	19.0087	47	60	60
Mobility Sample	6,172	52.7605	19.0832	48	60	60
Loan Size						
Dealscan Sample	24,692	18.7154	1.5585	17.7275	18.8262	19.8070
Full Sample	15,513	19.5867	1.2985	18.8262	19.6734	20.4356
Connectedness Sample	14,715	19.6065	1.2728	18.8262	19.6734	20.4356
Mobility Sample	6,172	19.7667	1.2398	18.9803	19.8070	20.6179

Panel B: Summary statistics of loan performance

Default						
Dealscan Sample	24,693	0.0512	0.2205	0	0	0
Full Sample	15,513	0.0656	0.2476	0	0	0
Connectedness Sample	14,715	0.0610	0.2394	0	0	0
Mobility Sample	6,172	0.0446	0.2063	0	0	0
Downgrades						
Dealscan Sample	24,693	0.8137	2.0172	0	0	1
Full Sample	15,513	1.0209	2.3155	0	0	1
Connectedness Sample	14,715	0.9990	2.2873	0	0	1
Mobility Sample	6,172	0.9227	2.1034	0	0	1
ROA						
Dealscan Sample	24,685	0.0109	0.0759	-0.1663	0.0280	0.0597
Full Sample	15,513	0.0104	0.0958	-0.0073	0.0301	0.0582

Connectedness Sample	14,715	0.0120	0.0949	-0.0061	0.0313	0.0591
Mobility Sample	6,172	0.0163	0.0867	-0.0026	0.0329	0.0601

Panel C: Summary statistics of firm characteristics

Variable	N	Mean	Std. Dev.	25^{th} pctile	Median	75^{th} pctile
Size						
Dealscan Sample	24,693	7.0943	1.7817	5.8484	7.0479	8.3145
Full Sample	15,513	7.8613	1.4617	6.9000	7.7676	8.8403
Connectedness Sample	14,715	7.8848	1.4421	6.9105	7.7884	8.8403
Mobility Sample	6,172	8.0828	1.4238	7.1112	7.9728	9.0036
Age						
Dealscan Sample	24,693	20.6940	15.9223	8	15	32
Full Sample	15,513	22.3843	16.9518	9	16	34
Connectedness Sample	14,715	22.3810	16.9664	9	16	34
Mobility Sample	6,172	22.9384	17.4761	9.5	16	35
Profitability						
Dealscan Sample	24,693	0.1256	0.0996	0.0832	0.1238	0.1698
Full Sample	15,513	0.1250	0.0799	0.0831	0.1184	0.1633
Connectedness Sample	14,715	0.1263	0.0786	0.0843	0.1198	0.1648
Mobility Sample	6,172	0.1272	0.0769	0.0852	0.1185	0.1670
Tangibility						
Dealscan Sample	24,693	0.3260	0.2378	0.1325	0.2667	0.4756
Full Sample	15,513	0.3235	0.2587	0.1007	0.2619	0.4975
Connectedness Sample	14,715	0.3216	0.2585	0.1002	0.2582	0.4924
Mobility Sample	6,172	0.3274	0.2702	0.0970	0.2557	0.5036
M/B						
Dealscan Sample	24,693	1.6654	1.0682	1.1152	1.3918	1.8722
Full Sample	15,513	1.6108	0.7818	1.1688	1.4266	1.7937
Connectedness Sample	14,715	1.6181	0.7855	1.1744	1.4342	1.8130
Mobility Sample	6,172	1.6384	0.8126	1.1773	1.4441	1.8676
Leverage						
Dealscan Sample	24,693	0.3414	0.2158	0.1913	0.3170	0.4605
Full Sample	15,513	0.3384	0.2025	0.1954	0.3125	0.4439
Connectedness Sample	14,715	0.3346	0.2013	0.1920	0.3095	0.4390
Mobility Sample	6,172	0.3291	0.1928	0.1919	0.3070	0.4377
Rated						
Dealscan Sample	24,693	0.5383	0.4985	0	1	1
Full Sample	15,513	0.6899	0.4625	0	1	1
Connectedness Sample	14,715	0.6932	0.4612	0	1	1
Mobility Sample	6,172	0.7328	0.4425	0	1	1

Table 3
Loan officer effects in loan contract terms
This table reports estimation results of bank- and loan officer-fixed effects in explaining loan contract terms, including loan spreads, covenants, and maturity. Panel A reports the incremental R^2s explained by bank and officer FEs from fixed effect when added to a baseline model. The specification of the baseline model is introduced in Equation 1. Panel B reports the results from the AKM method (introduced in Abowd, Kramarz, and Margolis (1999) and Abowd, Creecy, and Kramarz (2002)) as specified in Equation 2. The estimation is implemented using the Stata command "felsdvreg" as described in Cornelissen (2008). The unit of observation is a syndicated loan, bank, and loan officer. Column (1) examines loan spreads; Column (2) examines the number of loan covenants; Column (3) examines loan maturity. The rows for "F-test on FE" report the F-statistics of the null hypothesis that the estimated loan officer- or bank-fixed effects are jointly zero. See Appendix A for variable definitions. "# Movers" reports the number of loan officers that changed affiliation in the sample, "# Stayers" reports the number of loan officers that do not change affiliation, and "# Banks" is the total number of banks in the sample. Panel B reports incremental R^2s from fixed-effect models.

Panel A Incremental R^2s

Regression:		Adjusted R^2	Unadjusted R^2	Incremental R^2	
Dep. Var.: *Loan Spreads*					
(a)	Baseline	51.82%	52.10%		
(b)	Officer FE	67.38%	75.80%	(b) - (a)	23.70%
(c)	Bank FE	59.65%	61.44%	(c) - (a)	9.34%
(d)	Bank and Officer FE	68.38%	77.34%	(d) - (c)	15.90%
Dep. Var.: *Loan Covenants*					
(a)	Baseline	31.19%	31.58%		
(b)	Officer FE	58.17%	68.96%	(b) - (a)	37.38%
(c)	Bank FE	36.55%	39.38%	(c) - (a)	7.80%
(d)	Bank and Officer FE	61.58%	72.47%	(d) - (c)	33.09%
Dep. Var.: *Loan Maturity*					
(a)	Baseline	31.59%	31.98%		
(b)	Officer FE	44.03%	58.47%	(b) - (a)	26.49%
(c)	Bank FE	36.01%	38.85%	(c) - (a)	6.87%
(d)	Bank and Officer FE	44.69%	60.36%	(d) - (c)	21.51%

Panel B AKM Estimation

Dep. Var.:	(1) *Loan Spreads*	(2) *Loan Covenants*	(3) *Loan Maturity*
R^2 explained			
Officer FE	27.06%	43.27%	32.62%
Bank FE	7.42%	6.85%	3.28%
Officer FE/Bank FE	4.54	5.30	9.94
F-test on FE			
Officer FE	1.86***	2.83***	1.49***
Bank FE	1.98***	3.16***	1.45***
# Movers	891	891	891
# Stayers	4,403	4,403	4,403
# Banks	471	471	471
Unique officer-bank pair	6,430	6,430	6,430
Size	-23.0545***	-0.2160***	-3.2105***
	(-6.53)	(-5.60)	(-4.24)
Age	-0.1008	0.0015	-0.0949***
	(-0.65)	(0.64)	(-2.72)
Profitability	-82.1431	-0.4353	4.9067
	(-1.55)	(-0.83)	(0.62)
Tangibility	10.1957	-0.2135	-7.4180**
	(0.47)	(-0.82)	(-2.49)
M/B	-17.5786***	-0.0026	-0.6630
	(-4.80)	(-0.04)	(-1.10)
Leverage	102.5006***	0.5841***	8.3563***
	(5.45)	(2.63)	(2.76)
Rated	5.3942	0.1337	2.7009**
	(0.65)	(1.27)	(2.24)
Loan spread		0.0008***	-0.0075
		(2.60)	(-0.98)
Loan covenants	7.2321***		1.4149***
	(2.91)		(3.11)
Loan maturity	-0.2052	0.0045***	
	(-0.95)	(3.13)	
Loan size	-6.8006**	-0.0422*	2.4120***
	(-2.01)	(-1.81)	(3.66)
Lead arranger	29.5824***	-0.1412**	-0.1408
	(4.47)	(-1.98)	(-0.15)
LoanType FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Officer FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Observations	14,715	14,715	14,715

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

Table 4
Loan officer effects in loan performance
This table reports estimation results of bank- and loan officer-fixed effects in explaining loan performance. Panel A reports the incremental R^2s for bank and officer FEs from fixed effect models in addition to a baseline model. The baseline model is introduced in Equation 1. Panel B reports the results from the AKM method (introduced in Abowd, Kramarz, and Margolis (1999) and Abowd, Creecy, and Kramarz (2002)) as specified in Equation 2. The estimation is implemented using the Stata command "felsdvreg" as described in Cornelissen (2008). The unit of observation is a syndicated loan, bank, and loan officer. Column (1) examines the occurrence of loan default; Column (2) examines the extent of downgrade the borrower receives over the course of the loan; Column (3) examines borrower *ROA* over the course of the loan. "F-test on FE" reports the F-statistics of the null hypothesis that the estimated loan officer- or bank-fixed effects are jointly zero. See Appendix A for variable definitions. "# Movers" reports the number of loan officers that changed affiliation in the sample, "# Stayers" reports the number of loan officers that do not change affiliation, and "# Banks" is the total number of banks in the sample.

Panel A Incremental R^2s

Regression:		Adjusted R^2	Unadjusted R^2	Incremental R^2	
Dep. Var.: *Default*					
(a)	Baseline	23.30%	23.73%		
(b)	Officer FE	60.38%	70.61%	(b) - (a)	46.88%
(c)	Bank FE	30.32%	33.42%	(c) - (a)	9.69%
(d)	Bank and Officer FE	63.81%	74.06%	(d) - (c)	40.64%
Dep. Var.: *Downgrades*					
(a)	Baseline	28.69%	29.09%		
(b)	Officer FE	56.88%	68.00%	(b) - (a)	38.91%
(c)	Bank FE	32.82%	35.81%	(c) - (a)	6.72%
(d)	Bank and Officer FE	59.47%	70.96%	(d) - (c)	35.15%
Dep. Var.: *ROA*					
(a)	Baseline	39.55%	39.89%		
(b)	Officer FE	64.86%	73.93%	(b) - (a)	34.04%
(c)	Bank FE	43.02%	45.55%	(c) - (a)	5.66%
(d)	Bank and Officer FE	67.59%	76.77%	(d) - (c)	31.22%

Panel B AKM Estimation

Dep. Var.:	(1) *Default*	(2) *Downgrades*	(3) *ROA*
R^2 explained			
Officer FE	52.78%	47.08%	40.37%
Bank FE	3.71%	0.74%	6.56%
Officer FE/Bank FE	14.23	63.28	6.15
F-test on FE			
Officer FE	3.27***	2.67***	3.17***
Bank FE	3.23***	2.55***	2.95***
# Movers	891	891	891
# Stayers	4,403	4,403	4,403
# Banks	471	471	471
Unique officer-bank pair	6,430	6,430	6,430
Size	-0.0003	0.0926	0.0068**
	(-0.04)	(1.36)	(2.08)
Age	-0.0003	-0.0021	0.0001
	(-0.83)	(-0.40)	(0.71)
Profitability	-0.1307	-0.3079	0.2629***
	(-1.33)	(-0.34)	(5.37)
Tangibility	0.0987*	1.0146**	0.0072
	(1.92)	(2.09)	(0.35)
M/B	-0.0128	-0.2170***	0.0260***
	(-1.43)	(-2.65)	(6.22)
Leverage	0.0720	0.9709**	-0.0263
	(1.57)	(2.18)	(-1.59)
Rated	0.0191	0.5963***	0.0018
	(1.17)	(3.17)	(0.27)
Loan spread	0.0001	0.0006	-0.0000
	(0.79)	(0.88)	(-0.62)
Loan covenants	0.0025	0.1360*	-0.0030
	(0.35)	(1.88)	(-1.30)
Loan maturity	0.0012***	0.0173***	0.0000
	(3.76)	(6.09)	(0.31)
Loan size	-0.0075	-0.0216	0.0017
	(-1.46)	(-0.47)	(0.81)
Lead arranger	-0.0167	-0.2489*	0.0033
	(-1.09)	(-1.91)	(0.70)
LoanType FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Officer FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Observations	14,715	14,715	14,715

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

Table 5
Loan officer effects: MDV approach
This table shows the variations in loan contract terms and loan performance explained by loan officer-fixed effects and lender-fixed effects. We follow the fixed effect method employed by Bertrand and Shoar (2003). The test uses a sample that contains only movers, i.e., officers that have worked at more than one banks. We require all the officers in the sample to issue at least three loans. All regressions control for borrower and loan characteristics, year-fixed effects, and borrower industry-fixed effects. Columns 1 and 2 display F-statistics of loan officer- and lender-fixed effects.

Panel A Loan Contract Terms

Regression	(1) Loan officer FE	(2) Bank FE	(3) N	(4) Explained R^2	(5) Incremental R^2
Dep. Var.: *Loan Spreads*					
Baseline			6,172	53.95%	
Loan officer fixed-effects	2.100***		6,172	69.48%	15.53%
Bank fixed-effects		3.206***	6,172	63.29%	9.34%
Both fixed effects	1.727***	2.153***	6,172	73.47%	19.52%
Dep. Var.: *Loan Covenants*					
Baseline			6,172	30.50%	
Loan officer fixed-effects	2.072***		6,172	53.73%	23.23%
Bank fixed-effects		2.296***	6,172	41.21%	10.71%
Both fixed effects	2.274***	2.594***	6,172	62.55%	32.05%
Dep. Var.: *Loan Maturity*					
Baseline			6,172	34.98%	
Loan officer fixed-effects	1.394***		6,172	51.40%	16.42%
Bank fixed-effects		1.847***	6,172	43.29%	8.31%
Both fixed effects	1.269***	1.573***	6,172	56.73%	21.75%

Panel B Loan Performance

Regression	(1) Loan officer FE	(2) Bank FE	(3) N	(4) Explained R^2	(5) Incremental R^2
Dep. Var.: *Default*					
Baseline			6,172	23.82%	
Loan officer fixed-effects	1.958***		6,172	48.34%	24.52%
Bank fixed-effects		2.483***	6,172	36.37%	12.55%
Both fixed effects	2.301***	3.119***	6,172	59.25%	35.43%
Dep. Var.: *Downgrades*					
Baseline			6,172	29.95%	
Loan officer fixed-effects	2.015***		6,172	52.93%	22.98%
Bank fixed-effects		1.963***	6,172	39.39%	9.44%
Both fixed effects	2.237***	2.418***	6,172	61.02%	31.07%
Dep. Var.: *ROA*					
Baseline			6,172	39.93%	
Loan officer fixed-effects	1.763***		6,172	57.92%	17.99%
Bank fixed-effects		2.750***	6,172	50.69%	10.76%
Both fixed effects	1.746***	2.578***	6,172	65.07%	25.14%

t-statistics in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6
Controlling for banks' time-varying effects
This table reports estimated loan officer-fixed effects using the AKM method while controlling for bank-year fixed effects. The estimation is implemented using the Stata command "felsdvreg" as described in Cornelissen (2008). The unit of observation is a syndicated loan, bank, and loan officer. The sample includes all firms that have borrowed from the same bank prior to the loan of interest. Columns 1 through 3 report results for loan contract terms, and columns 4 through 6 estimate results for loan performance. The rows for "F-test on FE" report the F-statistics of the null hypothesis that the estimated loan officer- or bank-fixed effects are jointly zero. See Appendix A for variable definitions. "# Movers" reports the number of loan officers that changed affiliation in the sample, "# Stayers" reports the number of loan officers that do not change affiliation, and "# Banks" is the total number of banks in the sample.

Dep. Var.:	(1) *Loan Spread*	(2) *Loan Covenant*	(3) *Loan Maturity*	(4) *Default*	(5) *Downgrade*	(6) *ROA*
%$\hat{R2}$ explained						
Officer FE	28.85%	48.70%	33.81%	50.87%	43.44%	41.64%
Bank-Year FE	26.51%	18.23%	19.44%	16.02%	16.77%	12.66%
Officer FE/Bank-Year FE	1.09	2.67	1.74	3.18	2.59	3.29
F-test on FE						
Officer FE	1.94***	3.22***	1.53***	3.61***	2.80***	3.57***
Bank-Year FE	3.43***	3.46***	2.10***	3.27***	2.83***	3.55***
# Movers	1,656	1,656	1,656	1,656	1,656	1,656
# Stayers	3,642	3,642	3,642	3,642	3,642	3,642
# Bank-Year Observations	1,977	1,977	1,977	1,977	1,977	1,977
Unique officer-bank-year pair	8,481	8,481	8,481	8,481	8,481	8,481
Controls:						
Size	-25.2032***	-0.2217***	-3.2898***	-0.0041	0.0641	0.0076***
	(-6.75)	(-5.60)	(-4.05)	(-0.68)	(0.89)	(2.71)
Age	-0.0858	0.0015	-0.1012***	-0.0004	-0.0030	0.0000
	(-0.57)	(0.60)	(-3.05)	(-0.95)	(-0.58)	(0.27)
Profitability	-85.0274	-0.6075	5.1230	-0.1318	-0.1468	0.3077***
	(-1.51)	(-1.07)	(0.61)	(-1.16)	(-0.14)	(5.61)
Tangibility	4.5180	-0.1348	-7.5739**	0.0841	0.7468	-0.0027

	(0.20)	(-0.48)	(-2.48)	(1.54)	(1.49)	(-0.14)
M/B	-18.8238***	0.0172	-0.9066	-0.0119	-0.2134**	0.0230***
	(-5.24)	(0.28)	(-1.49)	(-1.28)	(-2.45)	(5.21)
Leverage	96.0404***	0.5111**	6.5696**	0.0865*	1.2915***	-0.0256
	(4.72)	(2.19)	(2.08)	(1.76)	(2.67)	(-1.51)
Rated	7.7155	0.1267	3.1434***	0.0141	0.5730***	0.0001
	(0.90)	(1.10)	(2.68)	(0.86)	(2.75)	(0.01)
Loan spread		0.0007**	-0.0095	0.0000	0.0002	-0.0000
		(2.12)	(-1.10)	(0.17)	(0.31)	(-0.43)
Loan covenants	6.4138**		1.2601***	0.0001	0.1084	-0.0024
	(2.37)		(2.63)	(0.02)	(1.37)	(-1.03)
Loan maturity	-0.2599	0.0036***		0.0010***	0.0164***	0.0000
	(-1.06)	(2.59)		(3.39)	(5.40)	(0.00)
Loan size	-5.7861	-0.0366*	2.2789***	-0.0068	-0.0255	0.0011
	(-1.52)	(-1.66)	(3.17)	(-1.36)	(-0.60)	(0.66)
Lead Arranger	26.6860***	-0.1844**	-0.0961	-0.0115	-0.2424	0.0012
	(3.63)	(-2.26)	(-0.09)	(-0.68)	(-1.58)	(0.24)
LoanType FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Officer FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,736	14,736	14,736	14,736	14,736	14,736

t-statistics in parentheses

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

Table 7
Movers across different banks

This table reports results from the AKM method when we restrict the movers in our sample to be those who move from lowly ranked banks to highly ranked banks, or from highly ranked banks to lowly ranked banks. Bank are ranked by the volume of loans they extend in a given year. We consider a bank to be lowly ranked if the amount of loans extended by the bank ranks at the bottom tercile of all our sample banks in a given year. We define a bank to be highly ranked if the loans extended by the bank ranks at the top tercile of all banks in a given year. Columns 1 through 3 report results for loan contract terms, and columns 4 through 6 estimate results for loan performance. The rows for "F-test on FE" report the F-statistics of the null hypothesis that the estimated loan officer- or bank-fixed effects are jointly zero. See Appendix A for variable definitions. "# Movers" reports the number of loan officers that changed affiliation in the sample, "# Stayers" reports the number of loan officers that do not change affiliation, and "# Banks" is the total number of banks in the sample.

Dep. Var.:	(1) *Loan Spread*	(2) *Loan Covenant*	(3) *Loan Maturity*	(4) *Default*	(5) *Downgrade*	(6) *ROA*
%R^2 explained						
Officer FE	35.81%	52.86%	37.33%	55.64%	35.78%	56.50%
Bank FE	4.98%	1.17%	5.78%	6.77%	5.51%	4.23%
Officer FE/Bank FE	7.19	7.06	6.46	8.22	6.49	13.37
F-test on FE						
Officer FE	2.18***	3.35***	1.63***	3.61***	3.01***	4.63***
Bank FE	2.82***	2.66***	1.49***	3.34***	2.36***	4.75***
# Movers	146	146	146	146	146	146
# Stayers	2,999	2,999	2,999	2,999	2,999	2,999
# Banks	262	262	262	262	262	262
Unique officer-bank pair	3,313	3,313	3,313	3,313	3,313	3,313
Controls:						
Size	-21.1190***	-0.2355***	-2.8203***	-0.0008	0.0868	0.0046
	(-4.97)	(-4.67)	(-3.33)	(-0.10)	(0.98)	(1.18)
Age	-0.1594	0.0022	-0.0367	-0.0008	-0.0053	0.0001
	(-0.84)	(0.68)	(-0.89)	(-1.29)	(-0.71)	(0.66)
Profitability	-39.0674	-0.7663	4.0962	-0.1345	0.8932	0.2132***
	(-0.60)	(-1.19)	(0.47)	(-1.14)	(0.80)	(4.51)

Tangibility	-1.7081	-0.1366	-5.0312	0.0947	0.7246	0.0214
	(-0.08)	(-0.40)	(-1.26)	(1.53)	(1.16)	(0.97)
M/B	-20.5408***	-0.0006	-0.3951	-0.0126	-0.2546***	0.0260***
	(-3.95)	(-0.01)	(-0.48)	(-1.19)	(-2.64)	(4.66)
Leverage	86.3179***	0.8590**	9.9990**	0.0730	1.5340***	-0.0433**
	(3.61)	(2.36)	(2.36)	(1.28)	(2.60)	(-2.09)
Rated	5.8668	0.0319	1.1664	0.0114	0.5283**	0.0042
	(0.64)	(0.21)	(0.70)	(0.49)	(2.24)	(0.51)
Loan spread		0.0008*	-0.0037	0.0001	0.0007	-0.0000
		(1.94)	(-0.32)	(1.31)	(0.93)	(-1.11)
Loan covenants	7.0379**		1.0584*	0.0035	0.1643*	-0.0040
	(2.23)		(1.65)	(0.38)	(1.78)	(-1.40)
Loan maturity	-0.0987	0.0032		0.0014***	0.0185***	0.0000
	(-0.33)	(1.64)		(3.60)	(4.92)	(0.34)
Loan size	-5.9944*	-0.0417	2.7972***	-0.0031	-0.0178	0.0016
	(-1.67)	(-1.53)	(3.54)	(-0.56)	(-0.38)	(0.83)
Lead Arranger	26.0519***	-0.2519**	-0.9925	-0.0053	-0.0684	0.0004
	(3.03)	(-2.19)	(-0.63)	(-0.25)	(-0.34)	(0.05)
LoanType FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Officer FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,284	7,284	7,284	7,284	7,284	7,284

t-statistics in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 8
Controlling for bank-borrower pairings
This table reports results from the AKM method when we control for the banks' selection of borrowers by including bank-borrower-fixed effects in the regressions. Columns 1 through 3 report results for loan contract terms, and columns 4 through 6 estimate results for loan performance. The rows for "F-test on FE" report the F-statistics of the null hypothesis that the estimated loan officer- or bank-fixed effects are jointly zero. See Appendix A for variable definitions. "# Movers" reports the number of loan officers that changed affiliation in the sample, "# Stayers" reports the number of loan officers that do not change affiliation, and "# Banks" is the total number of banks in the sample.

Dep. Var.:	(1) *Loan Spread*	(2) *Loan Covenant*	(3) *Loan Maturity*	(4) *Default*	(5) *Downgrade*	(6) *ROA*
%R^2 explained						
Officer FE	30.05%	15.67%	54.59%	66.39%	69.15%	111.03%
Bank-Borrower FE	23.82%	29.99%	33.52%	39.10%	50.80%	49.18%
Officer FE/Bank-Borrower FE	1.26	0.52	1.63	1.70	1.36	2.26
F-test on FE						
Officer FE	1.59***	5.25***	1.11***	9.88***	9.37***	10.72***
Bank-Borrower FE	1.96***	5.03***	1.29***	8.80***	9.81***	8.58***
# Movers	655	655	655	655	655	655
# Stayers	1,789	1,789	1,789	1,789	1,789	1,789
# Bank-Firm Pair	2,387	2,387	2,387	2,387	2,387	2,387
Unique officer-bank-firm pair	3,822	3,822	3,822	3,822	3,822	3,822
Controls:						
Size	3.8741	-0.1320	1.5634	0.0226	0.2758	-0.0033
	(0.16)	(-0.50)	(0.46)	(0.65)	(0.77)	(-0.27)
Age	-0.8747	-0.2542	4.4045	0.0037	0.8853	-0.0095
	(-0.03)	(-0.54)	(0.59)	(0.10)	(0.90)	(-0.92)
Profitability	40.4424	0.0376	14.8438	0.0180	2.5533	0.1709***
	(0.27)	(0.02)	(0.65)	(0.17)	(0.99)	(2.66)
Tangibility	-132.9922	-0.7197	5.9585	-0.1070	-3.2488	-0.0162

	(-1.11)	(-0.25)	(0.22)	(-1.01)	(-1.39)	(-0.22)
M/B	-20.8762	-0.0972	-5.4696	-0.0028	-0.0026	0.0253**
	(-1.17)	(-0.42)	(-1.17)	(-0.13)	(-0.01)	(2.37)
Leverage	86.2771	0.0392	33.3604	-0.1054	-0.1800	0.1030
	(0.71)	(0.02)	(1.60)	(-0.42)	(-0.07)	(1.29)
Rated	-70.0775	-0.3419	-2.3390	-0.0304	-0.5406	-0.0175
	(-1.36)	(-0.48)	(-0.39)	(-0.61)	(-0.93)	(-0.67)
Loan spread		0.0008	-0.0372*	-0.0004	-0.0023	0.0001
		(0.81)	(-1.88)	(-0.94)	(-0.96)	(1.25)
Loan covenants	13.8536		0.7602	-0.0049	-0.1533	0.0056
	(0.83)		(0.34)	(-0.20)	(-0.83)	(0.84)
Loan maturity	-0.6709	0.0008		0.0006	0.0175**	-0.0000
	(-1.23)	(0.33)		(1.25)	(2.55)	(-0.15)
Loan size	-2.8202	-0.0097	2.7830	-0.0104	-0.0865	0.0027
	(-0.18)	(-0.20)	(1.62)	(-0.97)	(-1.08)	(1.01)
Lead Arranger	11.6120	-0.3196	-0.3560	0.0100	0.1100	0.0007
	(0.46)	(-0.62)	(-0.05)	(0.57)	(0.50)	(0.07)
LoanType FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Officer FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,916	5,916	5,916	5,916	5,916	5,916

t-statistics in parentheses
*** p <0.01, ** p <0.05, * p <0.1

Table 9
Subsample analyses
This table reports estimation results of bank- and loan officer-fixed effects on loan contract terms and loan performance using subsamples of syndicated banks. The dependent variable in Panel A is loan spreads; the dependent variable in Panel B is loan covenants; Panel C reports results for loan maturity; and Panel D presents results for loan default. In each panel, column (1) reports results for large banks, i.e., banks whose market share in the syndicated lending market is above 1% in a given year; column (2) reports results for banks that have market share below 1% in a given year. Column (3) presents results for the subsample banks with above-median concentration in loans issued to different industries. Column (4) reports results for banks with below-median industry concentration. The rows for "F-test on FE" report the F-statistics of the null hypothesis that the estimated loan officer- or bank-fixed effects are jointly zero. See Appendix A for variable definitions. "# Movers" reports the number of loan officers that changed affiliation in the sample, "# Stayers" reports the number of loan officers that do not change affiliation, and "# Banks" is the total number of banks in the sample.

Panel A: *Loan Spreads*

	(1) *Large Banks*	(2) *Small Banks*	(3) *Diverse Industry*	(4) *Concentrated Industry*
%R^2 explained				
Officer FE	26.63%	30.41%	33.15%	24.53%
Bank FE	4.66%	10.21%	0.95%	8.27%
Officer FE/Bank FE	5.71	2.98	35.01	2.97
F-test on FE				
Officer FE	1.79***	2.01***	1.82***	2.05***
Bank FE	1.71***	2.17***	1.32**	1.94***
# Movers	270	417	265	277
# Stayers	2,139	2,773	2,341	2,100
# Banks	86	390	77	194
Unique officer-bank pair	2,728	3,686	2,907	2,721

Panel B: *Loan Covenants*

	(1) *Large Banks*	(2) *Small Banks*	(3) *Diverse Industry*	(4) *Concentrated Industry*
%R^2 explained				
Officer FE	47.28%	50.58%	48.03%	39.05%
Bank FE	5.39%	2.32%	7.38%	12.84%
Officer FE/Bank FE	8.77	21.80	6.51	3.04
F-test on FE				
Officer FE	2.85***	2.92***	2.91***	3.08***
Bank FE	3.26***	3.15***	2.93***	3.75***
# Movers	270	417	265	277
# Stayers	2,139	2,773	2,341	2,100
# Banks	86	390	77	194
Unique officer-bank pair	2,728	3,686	2,907	2,721

Panel C: *Loan Maturity*

	(1) *Large Banks*	(2) *Small Banks*	(3) *Diverse Industry*	(4) *Concentrated Industry*
%R^2 explained				
Officer FE	31.06%	38.93%	34.50%	34.47%
Bank FE	0.98%	5.19%	1.70%	4.70%
Officer FE/Bank FE	31.86	7.51	20.35	7.33
F-test on FE				
Officer FE	1.35***	1.61***	1.42***	1.47***
Bank FE	0.82	1.65***	1.27*	1.53***
# Movers	270	417	265	277
# Stayers	2,139	2,773	2,341	2,100
# Banks	86	390	77	194
Unique officer-bank pair	2,728	3,686	2,907	2,721

Panel D: *Loan Performance (Default)*

	(1) *Large Banks*	(2) *Small Banks*	(3) *Diverse Industry*	(4) *Concentrated Industry*
%R^2 explained				
Officer FE	53.22%	52.02%	57.42%	56.62%
Bank FE	1.47%	10.09%	1.61%	2.59%
Officer FE/Bank FE	36.26	5.16	35.78	21.85
F-test on FE				
Officer FE	3.07***	3.67***	3.22***	3.63***
Bank FE	2.04***	4.05***	2.26***	4.09***
# Movers	270	417	265	277
# Stayers	2,139	2,773	2,341	2,100
# Banks	86	390	77	194
Unique officer-bank pair	2,728	3,686	2,907	2,721

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

Table 10
Sub-period analyses
This table reports estimation results of bank- and loan officer-fixed effects on loan contract terms and loan performance from different sample periods. The first column describes the dependent variables in each test. Column (1) reports the sub-periods. Column (2) reports the incremental R^2 explained by officer fixed effects relative to the baseline model. Column (3) presents the incremental R^2 explained by bank fixed effects relative to the baseline model. Column (4) compares the relative explanatory power of officer fixed effects relative to bank fixed effects (Officer FE/Bank FE). The baseline model controls for firm characteristics, loan terms (other than dependent variable), borrower industry fixed effects, and year fixed effects.

Dep. Var.	(1) Sub-period	(2) Officer incremental R^2	(3) Bank incremental R^2	(4) Relative
Loan Spreads	1994–2003	19.29%	1.99%	9.69
	2004–2006	19.34%	0.62%	31.19
	2007–2009	18.57%	2.03%	9.15
	2010–2012	20.23%	2.06%	9.82
Loan Covenants	1994–2003	33.19%	2.82%	11.77
	2004–2006	36.00%	3.36%	10.71
	2007–2009	37.46%	3.42%	10.95
	2010–2012	37.26%	3.65%	10.21
Loan Maturity	1994–2003	16.12%	0.83%	19.42
	2004–2006	28.67%	2.73%	10.50
	2007–2009	20.09%	1.84%	10.92
	2010–2012	21.53%	1.96%	10.98
Default	1994–2003	35.62%	2.70%	13.19
	2004–2006	34.90%	1.46%	23.90
	2007–2009	43.35%	3.46%	12.53
	2010–2012	19.00%	3.83%	4.96

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

Table 11
Loan officer heterogeneity
This table reports the correlation of loan officers' lending styles. We first extract loan officer fixed effects using three-way fixed effects regressions using the method detailed in Abowd, Creecy, and Kramarz (2002). For detailed procedures, please see description in Table 4. After extracting loan officers' fixed effects in all aspects of lending activities, we examine the simple correlation between fixed effects.

	Loan Spreads	*Loan Covenants*	*Loan Maturity*
Loan Covenants	-0.0528***		
Loan Maturity	0.0605***	-0.0323**	
Default	0.1735***	0.0407***	0.0991***

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

Table 12

Loan officer heterogeneity

This table estimates the correlation of loan officer performance and the background characteristics of these loan officer. We regress the estimated fixed effects of loan officer on loan contract terms and loan performance metrics on loan officer background characteristics extracted from *LinkedIn* information. The independent variables are estimated officer fixed effects, collapsed at the officer level. *First Bank Size* is the market share of the first syndicated lender that an officer works at after graduation. *Business/Econ Degree* is an indicator that equals one if a loan officer majors in business (including Finance, Accounting, etc.) or economics. *Top School* is an indicator for whether an officer attended a top ten undergraduate or MBA program. *Female* is an indicator for whether the loan officer is female. *Cohort Year* is the year that a loan officer enters college. Column (6) reports the R^2 from the combined regressions. Loan officer fixed effects are estimated in a first stage regression following the method introduced in Abowd, Kramarz, and Margolis (1999) and Abowd, Creecy, and Kramarz (2002). The fixed effects are then normalized within each group of connected banks to have zero means.

Dep. Var.	Regression	(1) *First Bank Size*	(2) *Business/Econ Degree*	(3) *Top School*	(4) *Female*	(5) *Cohort Year*	(6) R^2
Loan Spreads	Separate	86.1982***	0.9792	13.4813**	0.3539	0.1130	
	Together	57.2989	13.4738	18.2356*	7.3121	0.0928	0.0157
Loan Covenants	Separate	0.8436**	-0.0361	0.0958	0.1082	-0.0033	
	Together	0.7754	-0.0240	-0.0634	0.0173	0.0008	0.0050
Loan Maturity	Separate	-10.3022**	0.3033	1.6043	0.6298	0.0875	
	Together	-12.8032**	-0.3003	1.3410	0.3633	0.0181	0.0089
Default	Separate	0.2094***	-0.0069	0.0035	0.0068	0.0003	
	Together	0.1742*	0.0115	-0.0166	-0.0135	0.0008	0.0075