How do borrowers find their banks? The value of individuals in bank relationship formation*

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Abstract

We investigate the role of individual commercial bankers in facilitating bank-borrower relationships. We find that after a relationship banker switches to a new bank, her former borrowers are almost twice as likely to initatie a new lending relationship with that lender, compared to the unconditional mean. These newly formed relationships extend beyond lending and include cross selling of bonds and other financial services unrelated to lending itself. The newly acquired borrowers bring an increase in deal volume of 0.66% across the various product groups. Bankers that close more deals, especially with clients for whom they are the only relationship manager, are more likely to switch. In a specific applicatino, we show that female bankers are leaving banks with female-unfriendly cultures and shift significant business to competing banks.

JEL Classifications: D22, G21, G32.

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1 Introduction

Bank loans are a primary source of capital for firms, and the choice of lender has major repercussions for borrowers. On the positive side, forming lasting lending relationships impacts both the availability and pricing of credit.[1] On the other hand, being connected to a lender also exposes borrowers to adverse shocks on the lender level. When the lender suffers losses, it can ration credit to its relationship borrowers.[2] Lending relationships therefore impact borrowers and transmit shocks from the financial to the real sector.

While it is well understood that lending relationships have a large impact on borrowers, there is much less evidence on how these relationships are formed, and what economic forces drive the matching of banks and borrowers. In particular, why would borrowers give up on the inherent value in an established lending relationship by switching banks? In this paper, we take a step towards answering this important question by studying the interaction between the labor market for commercial bankers and capital markets for borrower. We hypothesize that these bankers, who are the bank's source of soft information about borrowers (Berger and Udell, 2002) play a key role in matching borrowers to banks and that frictions in the labor market for bankers have consequences in capital markets.

Consistent with banks recognizing the ability of bankers to bring additional business, we find a strong positive relationship between the value of a banker's portfolio of relationships and the likelihood that the banker gets poached by a competing bank. A one standard deviation increase in the number of clients in a banker's portfolio (4.29) increases the chance that this banker switches to a competing bank by 0.65%, corresponding to a sizable 40% increase compared to the unconditional likelihood. Not all relationships are equally valuable. Larger clients produce more business and, therefore, revenue than smaller ones. Consistent with this intuition, we show that the number of larger clients is more important in predicting

[1] See, for example, (Diamond, 1984; Sharpe, 1990; Diamond, 1991; Rajan, 1992; Petersen and Rajan, 1994a; Berger and Udell, 1995; Bharath, Dahiya, Saunders, and Srinivasan, 2007; Ioannidou and Ongena, 2010a)

[2] For example, (Holmstrom and Tirole, 1997; Khwaja and Mian, 2008; Leary, 2009; Ivashina and Scharfstein, 2010; Chava and Purnanandam, 2011; Lin and Paravisini, 2013; Chodorow-Reich, 2014)

which bankers get poached than the number of small clients. These results are consistent with a wide anecdotal evidence of the dynamics between the labor market for bankers and relationship lending.[3]

If bankers use their existing relationship with borrowers to lure them along to new lenders, their ability to do so should be stronger if they are the sole contact person with the borrower. When we estimate the differential effect for clients that are exclusive to a single banker as opposed to those with multiple points of contact, we find that only clients that are exclusivele to a single banker predict banker turnover, and are subsequently following to the new bank. All these result are even more pronounced when we measure the value of a banker's portfolio as the number of prior deals (instead of the number of clients), with a one standard deviation increase in the number of deals by a banker's portfolio of clients being associated with a doubling of the unconditional rate of departure to a competing bank.

We next investigate if bankers indeed succeed in bringing their previous clients with them. We find that personal relationships between bankers and firms are a key factor in matching lenders to borrowers. After a commercial banker with an established lending relationship with a borrower switches from one bank to another, the incidence of the borrower following the banker to the new employer increases by 14% every year. This effect is economically sizable, representing an increase by a factor of almost 3 compared to the unconditional sample average.

Importantly, these results hold under tight controls including borrower-bank fixed effects which absorb all borrower-bank characteristics that are stable through time, such as industry, size, or corporate culture. Our results are therefore not driven by banks expanding both business and pool of bankers, business cycle fluctuations, or the general fit between a bank and a borrower. Instead, within-borrower-bank changes in having a personal relationship through a banker. In addition, bank-year and borrower-year fixed effects control for lender and borrower time specific trends in initiation new relationships. These controls rule out

[3] Appendix A provides extensive examples.

a wide range of alternative explanations for our findings, such as a lender expanding and both hiring additional employees and initiating new lending relationships. To the best of our knowledge, this paper is the first to document the importance of individual bankers in creating these important bank-borrower ties.

The relationships a lender can acquire by poaching a banker from a competitor have significant commercial value. After a banker switches to a new lender, that lender's deal volume with the banker's relationship clients increases by 35%. Importantly, these new clients do not just bring lending business, but also other types of underwriting services. We find that after a banker moves, the banker's former borrower also issues new bonds with the new lender. The ability to cross sell other underwriting mandates shows that lending relationships anchor the banking relationship more widely, creating additional benefits for banks. from acquiring new borrowers. The relationships acquired with a new banker are also long lasting. We find that lenders produce significant deal flow with borrowers that switched with a relationship banker for years after the initial deal.

In our final set of results, we investigate how one particular friction in labor markets spills over into capital markets. Using gender discrimination lawsuits filed against banks and the absence of female directors as proxies for less female friendly cultures, we find that banks with a less female friendly culture lose female bankers, and their clients.

Overall, our results show that there are important interactions between the labor market of individual bankers and the bank lending market.

We contribute to a number of papers on the importance of individual bankers in the US syndicated loan market (Herpfer, 2018; Bushman, Gao, Martin, and Pacelli, 2019). These papers show that bankers impact loans both through time invariant preferences or styles, as well as through the personal relationships they form with borrowers. These lending relationships give bankers a deep understanding of borrowers, and allow them to match borrowers to collaborate in joint ventures (Frattaroli and Herpfer, 2019). Consistent with these bankers having a sizable impact on lending decisions, there is evidence that they get punished after one of their borrowers defaults (Gao, Kleiner, and Pacelli, 2020).[4]

Our paper is further related to the literature on the formation of banking relationships. Borrowers tend to switch lenders more frequently when they are smaller (Ongena and Smith, 2001), and obtaining loans from a new lender is associated with favorable credit conditions (Gopalan, Udell, and Yerramilli, 2011) although these tend to worsen over time as lenders gain private information about borrowers, creating a "hold up" problem (Ioannidou and Ongena, 2010a; Schenone, 2010; Sharpe, 1990; Rajan, 1992; von Thadden, 2004) . Borrowers can mitigate this holdup issue by maintaining multiple lending relationships (Farinha and Santos, 2002). Karolyi (2017) finds that borrowers often switch lenders after the personal relationship between their executives and lenders is broken. In the paper closest to ours, Schwert (2018) shows that banks and borrowers match on observable criteria and that more bank relying borrowers match with more well capitalized banks. We add to his findings by showing that, apart from object firm and bank characteristics, there is a substantial human factor in the formation of bank borrower relationships.

2 Data

The following sections provide a description of our sample. We start by obtaining the employment history of bankers and their client portfolio from the SEC filings of all non-financial U.S. borrowers. Our sample starts in 1996, the first year of mandatory electronic filing, and ends in 2013. We complement this information with detailed loan data from LPC Dealscan, and supplement it with data on bond underwriting from Capital IQ.

[4]Individuals making connections between their networks is commonly observed in the business world outside the context of banking. Hacamo and Kleiner (2019), for example, show that managers allow their employers to hire talent from their personal network.

2.1 Bankers' personal relationships

We obtain data on the employment history of bankers from publicly available loan contracts. SEC Regulation S-K, Item 601(b), classifies loan contracts as "material events" that need to be disclosed by borrowing firms in their 8-K, 10-K, or 10-Q filing. We download these filings from EDGAR for all Compustat firms between 1996 and 2013. We then apply an algorithm that identifies loan contracts in these filings, and extracts the names and employers of the bankers from the signature pages of the loan contracts.[5] Figure 3 presents an example of one such page, with circles indicating the pieces of information extracted by our algorithm.

Christoph: I think it might make more sense to only have one observation at the new employer? Otherwise we really bias ourselves against finding our result? There is a strange autocorrelation where after the switch, banker hired can never take the value 1 anymore for this banker-bank combination? Only problem with that setup is that some bankers might change more than once and we could only do this transformation of the data for their first switch. The pre- post collapsed table is a very important robustness test for this.

[5] More detailed descriptions of the data, as well as examples and quality checks of the dataset can be found in Herpfer (2018) and Gao et al. (2020).

Figure 1: Example of banker's employment history

Year	*Banker*	*Bank*	*Borrower*	*Banker hired*	*Client portfolio*	*Tenure*
2000	*Anne*	*Bank of America*	*GM*	0	*GM*	1
2001	*Anne*	*Bank of America*	–	0	*GM*	2
2002	*Anne*	*Bank of America*	–	0	*GM*	3
2003	*Anne*	*Bank of America*	*HP*	0	*GM; HP*	4
2005	*Anne*	*JPMorgan*	*GM*	1	*GM; HP*	1
2006	*Anne*	*JPMorgan*	–	0	*GM; HP*	2
			...			
2009	*Anne*	*JPMorgan*	*3M*	0	*GM; HP; 3M*	5

For each loan we obtain the name of the banker and the name of the bank for which the banker is signing.[6] Figure 1 shows an example of a banker's employment history. We start from the loans that we extract from the SEC and expand the dataset to obtain a balanced panel: E.g., whilst working at Bank of America, banker Anne signs a loan with GM in 2000 and one with HP in 2003. We assume that a banker works at the same bank for all years between different loans: E.g., Bank of America will employ banker Anne for all years from 2000 to 2003, even if we do not observe deals in all those years.

We define the indicator *Banker hired* as the first year a banker appears on a loan contract for a new bank. The client portfolio of a banker consists of all firms for which the banker's name appears in the loan documents. We will refer to these clients as firms with whom a banker has a "*personal relationship*". Most large corporate loans are syndicated between various lenders. Our analysis only assigns clients into a banker's portfolio if the banker was

[6]In our main analyses we do not require to find a match between the loan contract we download from EDGAR and Dealscan as our algorithm extracts contracts not in DealScan (Herpfer, 2018). These are often amendments and extensions of existing loans which are not a focus of DealScan, but allow us to more precisely pinpoint the points of time at which bankers switch between employers. Our results remain unchanged if we restrict the sample to the deals for which we have an overlap with Dealscan.

working for the lead arranger of the syndicate, as these bankers mostly are the ones that directly interact with borrowers and form personal relationships with clients. Crucially, the banker carries over her client portfolio when she gets hired by the new bank. The tenure of the banker counts the number of years that she is been working for the same bank.

- Table 1 -

Panel A of Table 1 provides summary statistics of the banker's client portfolio characteristics. The sample is at a banker-year level and covers over 20,000 bankers that collectively switch employer 1,066 times, while spending an average 3.7 years at one bank. Only 19% of the bankers in the sample are female. Christoph: This feels a little off? 3.7 years per bank and 20,000 bankers implies 74k banker-year obs. Need to add another 4k from those bankers that appear at multiple banks brings us to 80 k? Can we run a robustness test where we only consider bankers that switch at some point?

In the first part of our analysis we ask which characteristics of the bankers' client portfolio make changing banks more likely. We start by computing the total number of clients with which the banker had a relationship at a given bank. To distinguish between small and large clients, we obtain each borrower's total assets from Compustat. We define a large client as having total assets above the 75-th percentile of sample firms during a given year. Small clients are those with assets below the 25-th percentile. The average banker has a personal relationship with three clients, half of which are large.[7]

To investigate whether bankers have less ability to make clients follow them to new banks if the client ahs multiple contact people at the bank, we define an indicator for clients that have deals with multiple bankers at the same bank, i.e., "*Multiple contact*" clients. "*Single contact*" clients are defined as those that always interact with the same banker when borrowing from a bank. The average banker has 1.5 single contact clients and 1.6 multiple contact clients.

[7] Only 3% of borrowers are classified as small, which is in line with the idea that the syndicated loan market is dominated by large borrowers.

We also calculate the number of specific loans issued by each banker, as well as those that the banker closes with small and large clients. We also count the number of deals closed with single and multiple contact clients. The average banker closes an average of 4.14 deals. CH: I think we might want to drop this description and the variables if we don't use them: , 47% of which are with large clients and 3% with small clients. Bankers close an average of 2 and 2.5 deals with single and multiple contact borrowers respectively.

Panel B of Table 1 shows summary statistics at a bank-year level. On average, a bank employs 16 bankers, each of which closes 1.5 deals per year. A bank lends to an average of 29 clients, out of which 2.7 are large and 0.3 small. Less than 1% of banks' clients is covered by multiple bankers. For all those numbers, it is important to keep in mind that we only observe a fraction of the actual loan volume issued, since many borrowers are private therefore do not file with the SEC.

2.2 Banks' client portfolio

In the second part of the paper, we want to understand whether banks profit when a new banker starts working for them. To this end, we start with the sample of all Compustat firms and obtain all syndicated loans that these firms take out from Delascan for our sample period. We complement this with the underwriting of corporate bonds from CapitalIQ. We refer to "deals" as any occurrences of either loans or bonds being issued by the firm.

In a second step, we manually merge these datasets to the bankers sample from the SEC.We posit that when a banker changes employer, she will bring her personal relationships over to the new bank. An example is illustrated in Figure 2 below. We start by creating bank-firm pairs for all firms that were in the client portfolio of the banker that switches (e.g., GM and HP). We define the ever treated indicator Rel_acq that takes the value of one for all these pairs, for all years after the banker joins the bank. To account for the fact that relationships decay over time, we define the indicator Rel_acq^{5yr} that is set to missing after the fifth year following the switch. To be even more conservative, we define the absorptive treatment indicator Rel_acq^{abs}, that is set to missing after the first year following the switch. In this way we essentially consider as treated only deals that happen the year the banker switches.

Figure 2: Example of bank's client portfolio
Banker Anne switches to JP Morgan in 2005 and JP Morgan "acquires" her personal relationship to GM and HP, Anne's old clients from her time at Bank of America.

$Year$	$Bank$	$Firm$	$Deal$	Rel_acq	Rel_acq^{5yr}	Rel_acq^{abs}	$Initiation$
2004	$JPMorgan$	HP	1	0	0	0	1
2005	$JPMorgan$	HP	0	1	1	1	0
2006	$JPMorgan$	HP	0	1	1	–	0
			...				
2010	$JPMorgan$	HP	1	1	–	–	0
2004	$JPMorgan$	GM	0	0	0	0	0
2005	$JPMorgan$	GM	1	1	1	1	1
2006	$JPMorgan$	GM	0	1	1	–	0
			...				
2010	$JPMorgan$	GM	1	1	–	–	0

It could be that the results we observe are mechanical, since we identify bankers that switch using deals that they sign at a new bank. To make sure that this is not the case we will re-run all of our tests using the treatment indicators $Rel\_acq\_nofirst$, $Rel\_acq\_nofirst^{5yr}$, and $Rel\_acq\_nofirst^{abs}$, defined as before but ignoring the first deal at the new bank.

Not all firms with whom a bank acquires a personal relationship by employing a new banker are additions to the client portfolio of the bank. In our example in Figure 2, JP Morgan had already closed a deal with HP *before* banker Anne joined the bank. In contrast, the first deal JP Morgan closed with GM happened after banker Anne joined the bank and brought over his personal relationship to the firm. To make sure that we attribute only the latter type of deals to the new banker, we define the indicator variable *Initiation* that takes the value of one for the first deal that the bank signs with a firm or if the last deal occurred more than five year in the past. For robustness, we also define *Initiation_strict* that captures only the first interaction between a bank and a firm.

The final dataset is then expanded to obtain a balanced panel for all firm-bank pairs with whom the bank had a deal or acquired a personal relationship through a banker.[8] Our sample covers some 55,000 bank-firm pairs between 1996 and 2013.

- Table 2 -

Panel A of Table 2 presents summary statistic at the bank-firm-year level. The average bank acquires relationships to about 3% of its client portfolio. This figure becomes 1.5% and 0.3% if we consider only the five-year or the one-year period after the switch of a banker. Only 5.2% of all bank-firm interactions are accounted for by deals with first-time clients.

To measure the deal volume that the bank generates thanks to the personal relationships, we sum the value of all deals that a bank closes with a firm during a year. Panel B of Table 2 shows summary statistics for bank-firm-years when deals occur. During such periods, a bank signs an average 1.7 deals with a client. The average deal volume is USD 828 million. When looking at syndicated lending and bond underwriting in isolation, the deal size is USD 418 million and USD 280 million.

Panel C presents a brief overview of the balance sheet information of the banks' clients. The average firm is large, with total assets of about USD 7 billion, leverage of 57%, EBITDA of USD 227 million, profitability of 5%, and a ratio of intangibles to total assets of 14%.

[8]While this increases the number of observations substantially, it works against us finding a positive impact of a banker switching on the client portfolio and loan volume since we create bank-firm pairs for years when *no* deals occur. Moreover, in this way we are not overweighting banks that close more deals. Our results are robust to estimation on a collapsed borrower-bank panel that features just a single observation for each borrower-bank pair for the periods before and after a personal relationship is acquired, respectively. These results can be found in Table A6.

3 Results

This section we first investigate which characteristics of a banker's portfolio correlate with a higher probability of switching banks. Second, we take the perspective of the bank that acquires client relationships of the banker: Do the banks benefit from the banker's switch? Finally, we explore what types of deals are driving these results.

3.1 Which bankers change employer?

If individual bankers are the key to maintaining borrower relationships for a bank's existing clients, poaching bankers from another lender can be a fast way for a bank to obtain new lending relationships. Appendix A provides large amounts of anecdotal evidence that supports this conjecture. We posit that the composition and value of a banker's client portfolio is an important driver of the likelihood of getting poached, and switching employer.

To examine the importance of the client portfolio in our sample, we estimate specification 1. The independent variable is $\textit{Banker hired}_{i,t}$, an indicator variable for the year t when banker i starts working at a new bank, on $\#Clients^{\theta}_{i,t-1}$, various measures of the number of clients the banker had in her portfolio in the previous year. Even columns include bank (γ_j) and year fixed effects (δ_t) to control for time invariant bank characteristics and general time trends. Odd columns present specification with bank×time fixed effects to account for the possibility that a bank might want to expand in a given year and is therefore hiring bankers. Intuitively, these specifications therefore compare the likelihood that a certain bank hires one of two bankers at the same point in time, and asks if each banker's client portfolio composition impacts their likelihood of getting hired. Standard errors are clustered two-dimensionally at the bank and banker level to account for arbitrary correlations in error terms within banks across time, and within years across bankers.

$$\textit{Banker hired}_{i,t} = \beta_1 \#Clients^{\theta}_{i,t-1} + \beta_2 \gamma_j + \beta_3 \delta_t + \epsilon_{i,t} \tag{1}$$

Panel A of Table 3 reports the results of this regression. The first column shows that having a personal relationship with one additional client correlates with an increase in the switching probability by 0.2%. When we introduce bank×year fixed effects in column two, the coefficient becomes 0.15%. This effect is economically large. A one standard deviation increase in a banker's number of portfolio firms (4.29 clients) corresponds to a roughly 50% increase in likelihood of getting hired by a bank, compared to the unconditional probability.

- Table 3 -

In columns (3) and (4), we investigate whether it is not just the number, but also the size of clients in a banker's portfolio that matter for their propensity to get poached by competing lenders. There is no clear theoretical prediction if smaller clients matter more or less than larger ones. On the one hand, relationship lending is most important for small firms (Petersen and Rajan, 1994b), which means bankers might be more successful in moving their small clients to a new bank. Therefore, having more small clients in ones' portfolio could increase the likelihood of the borrowers following the banker to the new bank. On the other hand, a banker with many larger clients might be more attractive to new banks, as larger clients potentially generate more, and more lucrative deals. Which of these channels dominates is ultimately an empirical question, and we test these hypothesis by separately estimating the effect of the number of small and large clients in columns 3 and 4. For the purpose of this analysis, we define clients are those with assets below the 25-th percentile in our sample.

The results in column 3 suggest that both the number of small and large clients impact the likelihood of a bankers witching banks. The coefficient estimate for the number of small clients is nominally larger than that for large clients, at 0.63 as opposed to 0.25 for large clients. However, since there are significantly fewer small borrowers in our sample, a one standard deviation increase in the number of large clients increases the likelihood of switching by 1.1%, about five times as much as a one standard deviation increase in the number of small clients. Once we add bank×year fixed effects in column 4, the coefficient on small clients drops to 0.34 and is no longer statistically significant, while that on large clients actually increases to 0.17, and remains statistically highly significant. In sum, these results indicate that a portfolio of larger clients makes bankers particularly attractive targets for other lenders in the labor market.

CH: A referee will likely push us on the definition of "small" here, at 25% of assets (and 3% of the sample). Any chance these results go through with a 50% cutoff, or maybe even better, in continuous form where we take the avg size of clients inside the portfolio?

In columns (5) and (6) we distinguish between clients that have a relationship with multiple bankers and those for which the switching banker is their single contact at the bank.

Firms with multiple banking relationships are less likely to switch banks (Ioannidou and Ongena, 2010b). and are more shielded against bank-specific risks (Degryse, Masschelein, and Mitchell, 2011). Hence, we assume that such firms are also less likely to follow the banker to a new bank. It is cool to cite the literature, but I think the connection is not 100% there. These papers are about multiple bank relationships, our hypothesis is about multiple banking relationships. I re-wrote. (I understand the multi contact variableto mean "multiple bankers within a bank", consistent with page 7)

Some firms interact with more than one banker within their lender. The literature on institutional relationships between banks and borrowers has found that spreading lending relationships, and hence information, between multiple lenders reduces the importance and bargaining power of each individual lender. In our context, we hypothesize analogously that a banker has less sway over a borrowers if the borrower has multiple points of contact within the bank. If this is the case, then we would expect that relationships to borrowers for which a banker is the sole point of contact are particularly valuable.

Our results in columns 5 and 6 of Table 3 are consistent with this hypothesis. A one standard deviation increase in the number of single contact clients correlates with a probability of getting hired each year that is about 1.1% higher, almost double the unconditional likelihood. In contrast, the coefficient estimates for the number of clients clients with multiple banker relationships are economically and statistically insignificant in both specifications.

We provide a number of additional tests that support these results in Appendix A. In Appendix Table A3, we perform the same tests but using the number of deals instead of the number of clients. We do this in an attempt to account for the volume of business that the banker generates.All results from of these regressions are consistent with the previous findings both in terms of economic magnitude and statistical significance.

Taken together these results suggest that having personal relationships with more clients is beneficial for the probability of changing employer. Particularly important are large clients and those for whom the switching banker is the single contact to the bank.

3.2 Banks benefit from poaching banker from competitors

We now investigate the perspective of the bank and ask if hiring new bankers from competitors actually benefit the lender. We start by showing that hiring a banker with a personal relationship to a specific firm indeed increases the likelihood to initiate new business relationships with this clients.

3.2.1 Banks expand their client portfolio after a new banker joins

For this analysis, we create a balanced panel of all bank-firms in our sample, as in Figure 2. When we observe a banker switching to a new bank, we treat all firms with whom the banker had contact at the old bank as personal relationships that the bank "acquires". We set the relationship acquired variable to one for all these bank-firm pairs in the years after the switch. We then estimate regression 2, where the dependent variable is $Inititaiton_{i,j,t}$, an indicator that takes the value of one if bank i has the first deal with firm j in year t, or if the last deal with firm j was more than 5 years ago. We also define $Inititaiton\_strict_{i,j,t}$ that identifies only the first deal with firm j. A deal can be either a syndicated loan, a bond, a SEO offering, or an M&A advisory contract.

$$Initiation_{i,j,t} = \beta_1 Rel\_acq^{\theta}_{i,j,t} + \beta_2\gamma_i + \beta_3\phi_j + \beta_4\delta_t + \epsilon_{i,j,t} \quad (2)$$

The explanatory variable is the treatment identifier $Rel\_acq^{\theta}_{i,j,t}$ that identifies all firms j for which bank i has acquired a personal relationship at time t. θ differentiates between the various types of treatment, ever treated (Rel_acq), treated within the last five years (Rel_acq^{5yr}), and absorptive treatment (Rel_acq^{abs}), i.e., treated only during the year of the switch. We further saturate the model with various types of firm, bank, and time fixed effects ()γ_i, ϕ_j, and δ_t). Standard errors are clustered two-dimensionally at the firm and lender level. Table 4 reports the regression results. CH: since we use the "treatment" language, we might be forced to show parallel trends (that's a common ref response to reading the word "treatment")

- Table 4 -

The coefficient estimate on Rel_acq in column (1) shows that acquiring a personal relationship increases the initiation likelihood by 7% CH: The summary statistics report initiation as percent - is it an indicator here?) if so, should report it as indicator in sum stat I think? per year. This increase represents an economically sizable effect, more than twice the unconditional mean of initiation of 5.2%. CH: I am not sure if we can do the "a one sd increase in rel acquired leads to... calculation here. The sd is 16, the coefficient is 7, which implies a close to 100% chance of getting the client. But I am also not sure about how to think of this back of envelope calc in the presence of all our FE This specification includes firm fixed effects, which absorb all time invariant firm level heterogeneity, such as certain firms being more likely to raise capital from new banks and having more relationships to bankers. Year fixed effects control for time varying effects, such as periods with stronger economic growth being associated with more switching of bankers as well as borrowers. Finally bank fixed effects control for time invariant heterogeneity in the propensity of banks to acquire both new clients and new bankers. Moreover, the data structure is very conservative. We code *all* firms with whom a banker had deals in the past - regardless of when - as acquired relationships in *all* years after the banker joins.

One potential alternative explanation to this finding could be that there are unobservable, time invariant characteristics that make the match between a specific firm and bank a particularly good match, while also making the bank an attractive employer for bankers. For example, a bank might specialize in a certain industry or a certain subset of the lending market that both make it attractive to bankers and borrowers in that industry . In column (2), we address this issue by introducing a firm×bank fixed effect. Economically, this means that we compare the same firm-bank pair over time, before and after a banker with a prior relationship to the firm switches to the bank. These fixed effects also absorb all time invariant characteristics, such as size, geographic concentration, or culture, on both the firm level and the bank level. This includes pair specific characteristics, for example the bank being specialized in the firm's industry. The coefficient of interest remains positive and significant in this specification.

One concern could be that a bank expanding its operations is both hiring more bankers, and acquiring new firms. In column (3) we therefore include bank×year fixed effects that capture the average propensity of banks to acquire new firms (and new bankers). The variation we exploit in this specification is therefore comparing firms that had a personal relationship to a banker acquired by the bank in a given year to those firms for which no banker was acquired. Intuitively, these fixed effects therefore control for loan *supply* conditions.

Finally, we also include firm×year fixed effects. These absorb any time varying firm characteristics, such as a firm seeking loans from new lenders to finance an acquisition. Importantly, these firm-year fixed effects also nest industry year fixed effects that control for confounding factors such as strong growth within a certain industry. Effectively, we are now comparing the propensity of a certain firm to initiate a new lending in a given year, choosing between a lender that recently acquired a relationship banker and a lender that has not. Intuitively, these fixed effects control for loan *demand* conditions (Jakovljević, Degryse, and Ongena, 2020). Even with this tight econometric specification, the effect of acquiring a personal relationship to a firm on the probability of initiation is positive, economically meaningful, and highly statistically significant: A one standard deviation increase in *Rel_acq* (.17) correlates to a 2% increase in initiation probability (10% of a standard deviation). CH: I now better understand these numbers. I think we can improve readability and clarity a lot by making numbers identical, i.e. always report % or always report digits. Personally,, I would like to have all indicators as percentages bc most numbers and coefficients are very small, sow ould improve presentation a lot. What do you think?

In columns (4) and (5) we account for the fact that the relationships that a bank acquires decay over time. Specifically, we attribute initiations to acquired relationships only within a time-frame of 5 years and 1 year respectively. Our results remain virtually unchanged even when using the most conservative treatment definition: Acquiring a new client relationship makes initiation 12% more likely in the 5-year period after the banker switches and 7% more likely in the year of the switch.

It Appendix Table A4 we restrict the definition of the dependent variable such that it includes only relationships with new clients. Our results remain virtually unchanged, regardless of the treatment definition. Moreover, since we identify bankers changing banks using deals that they sign at the new employer, one concern could be that there is a mechanical component to our estimates. CH: I rewrote the sentence before - compare it to the last version. This was a very painful lesson I had to learn over the last few years in how to correctly phrase and "hedge" these limitations In Appendix Table 5 we replicate all our previous results whilst dropping the first deal that the bankers sign when they switch banks. Our results remain robust even in this specification. In sum, it seems that banks expand their client portfolio with firms for which they acquire personal relationships.

Not all borrowers rely on personal relationships to the same degree. Smaller, more opaque borrowers of worse credit quality often rely more heavily on relationship lending compared to other borrowers CITE. We therefore hypothesize that those borrowers are more likely to follow their bankers to new banks. We formally test this hypothesis in Table 5.

- Table 5 -

Specifically, we interact our measure of a bank having acquired a banker with a personal relationship to a borrower with one of three proxies for the borrower's opacity. First, in column (1), an indicator if the borrower is rated as "junk", i.e. non investment grade. Second, in column (2, an indicator for whether the borrower's intangibles-to-asset- ratio is above the median, and finally, in column (3), we interact rel_acq with an indicator for small firms with assets below the median. We find that, in all three cases, the main finding remains robust that a lender that acquires a personal relationship to a borrower by hiring a connected banker is significantly more likely to initiate a business relationship with the borrower. In addition, we find that the interactions of all three proxies for opacity load positive and statistically significantly. The economic magnitude of these estimates is substantial and represents an increase of between roughly 50% and 100% compared to the baseline estimate. Borrowers that rely more heavily on relationship lending therefore are more likely to follow their bankers to new lenders.

3.2.2 Banks increase deal volume to clients acquired through bankers

Acquiring bankers and their portfolio of relationships is not an end in itself. Ultimately, banks aim to sell services to these borroers. In this section, we investigate if acquiring personal relationships also lead to an increase in the volume of deals that the bank closes?

$$Log\ Deal\ Volume_{i,j,t} = \beta_1 Rel\_acq^{\theta}_{i,j,t} + \beta_2\gamma_i + \beta_3\phi_j + \beta_4\delta_t + \epsilon_{i,j,t} \tag{3}$$

To answer this question we run regression 3, where the dependent variable is the logarithm of the total deal volume that the bank i signs with firm j during year t. The main explanatory variable, $Rel\_acq^{\theta}_{i,j,t}$, is the indicator for the firms j where bank i has acquired a personal relationship as of time t.[9]

- Table 6 -

Panel A of Table 6 shows the results of estimating regression 3. We find a positive and significant effect of acquiring personal client relationships on the total deal volume with these clients. The point estimate in column (1) implies that a one standard deviation increase in *Rel_acq* (0.06) correlates to an increase in deal volume of ca. 4% each year. From column (2) we can establish that accounting for time-invariant characteristics of the bank-firm pair (e.g. cultural proximity or industry specialization of the bank) does not change our results. Columns (3) and (4) show that the same holds when we account for loan supply and demand characteristics respectively. Columns (5) and (6) confirm our findings for a more conservative definition of the treatment identifier. Finally, Appendix Table A8 shows that all of these findings are robust to dropping the first deal that the bankers close at the new bank.

In Panel B of Table 6 we document the interaction effect of initiating a new client relationship whilst acquiring a personal relationship to that client. This shows that the increase in deal volume we observe actually comes form clients with whom the bank had no business in the past. The comparison group in this specification will be all deals that the bank signs with existing customers for which no relationship has been acquired. Compared to these firms, a one standard deviation increase in $Initiation$ (0.23) translates in a boost of 0.74 standard deviations in deal volume with new clients (with whom *no* personal relationship exists).

The coefficient of *Rel_acq* captures the business that a bank generates with *existing*

[9]For this part of the analysis we drop all firm-bank pairs for which a bank acquires a relationship but never closes a deal with. We do this since we are interested in the deal volume generated by the banker's relationships relative to the *existing* deals. We need to thinking a little more about this. So we limit the sample to either a) firms for which there were deals but never relationships and b) relationships and deals. We exclude relationships without deals? I think we had thought this through before but reading it with a cold eye it feels odd. In particular, why is this an issue for deal size but not for initiation? In general, we probably need to have a small appendix where we explain our sample (we definitely thought a lot about this a year ago when we started but it's not in the paper right now I think?)

clients for which an additional personal relationship was acquired. The negative coefficient means that, if anything, acquiring such relationship is not helpful to generate additional business.

The interaction term $Rel\_acq \times Initiation$ measures the boost in deal volume attributable to new clients for which a personal relationship has been acquired. The total effect corresponds to 28% $[= (1.64 - 0.29)/4.91]$ of the effect of initiating a new client relationship. Hence, when a bank manages to win over a firm for which it acquired a personal relationship in the past it will generate almost a third more deal volume compared to the scenario when a bank brings over a firm without having a personal relationship first.

The results in columns (2) to (4) show that the results are robust to introducing controls for time-invariant bank-firm-pair characteristics, as well as for loan demand and supply factors. Models (5) and (6) show that restricting the treatment window to five years or even to one year does not have a meaningful effect on our results.[10] Appendix Table A9 confirms that our results are robust to using a more conservative definition of $Initiation$ that identifies only new clients. In unreported analyses we can also confirm that the effects are even stronger if we restrict the sample to firm-bank-years where at least a deal is closed. We can thus ensure that the findings are not driven by existing clients not taking out loans.

These results show that banks do not only expand their client portfolios after they acquire personal relationships to firms, but also increase the volume of deals that they close with these clients. This is particularly the case for *new* clients for which a relationship has been acquired in the past.

OK, so I think this section is our weakest one right now. The data selection will raise flags and interpretation of coefficients is not easy. Let's think about this. Maybe we keep only panel B and move panel A into the appendix? Or we kick it all to the Appendix? It feels as if it really does not provide a lot of new info over the initiation results, and raises

[10] In the last column the coefficient of Rel_acq^{abs} becomes positive and significant. This is due to us treating all years after the relationship has been acquired as missing. In doing so we do not "penalize" the bank for the years after the relationship has been acquired and there were no deals.

flags that could contaminate the rest of the paper? I now think I remember that the key problem is that initiation takes value 1 for all years, but deal volume fluctuates (naturally). So we really penalize ourselves bc each "zero" counts over and over again, and even for a "one", i.e. where deals happen, we have 4 zero observations for each 1. I think we need to present these results in the pre- post format as Table A5. So split A5, put the deal volume in here, keep the initiation pre- post as robustness A5. Than move the "deal cathegory" regressions (current table 6) to pre-post format. Also, we should make sure we always have the same number of obs in regressions (we lose some due to fixed effects.) the way to do that is to run once the most restrictive regression (with all FE) before the actual table, and the use the command "keep if e(sample) == 1". this limits the sample in all regressions to the most restrictive one, it's just a bit more clen bc we have no changes in sample across specs.

3.2.3 Do banks cross-sell other products?

Re-do with pre/post. Decide if we want to keep presenting SEO if results remain insignificant. Consolidate into single table with two columns each?

In Table 7 we investigate if the relationships acquired through bankers allow banks to cross- sell products other than commercial loans. We separately estimate specification 3 for the samples of syndicated loans, bonds, and SEOs. For each sub-sample we keep only the observations where either no deal occurs or where at least one syndicated loan, one bond, or one SEO was closed respectively. The dependent variable in Panel A is the logarithm of the total syndicated loans taken out by a firm. In Panels B it is the logarithm of the total bonds and in Panel C that of the total SEOs the bank underwrites.[11]

- Table 7 -

Column (1) of Panel A and B shows that a one standard deviation increase in *Rel_acq* is associated with a respective increase in 1.3% and 3.5% in syndicated loans and bond

[11]For brevity we do not report the results for M&A deals since the sample is quite small and the coefficients are insignificant. This is because (a) we require the deal volume to be public and (b) the sample overlap is small.

underwriting respectively. While small, the point estimate roughly corresponds (for the average deal) to an additional USD 10 million and USD 33 million in syndicated loans and bonds that a bank closes with a firm during a single year.

The coefficients in Panel A remain positive but become insignificant after we introduce firm $\times$ bank and bank $\times$ year fixed effects. However, after we account for loan demand in column (4), the effect is again significant. This stresses the importance of comparing the borrowing decision of a firm that chooses between two banks, one where it knows the banker from previous interactions, and one to which it has no connection. The last two columns highlight that our results are robust to using a stricter treatment identifier. In Panel B, all coefficients are positive and highly significant. This highlights the fact that our results are not driven exclusively by the syndicated loan market but extend to bond underwriting as well.

In contrast, from Panel C we gather that the underwriting of Seasoned Equity Offerings is not at all influenced by personal relationships. This finding is in line with the idea of "Chinese walls" between the commercial lending and investment banking departments.[12]

3.2.4 Are relationships long-lasting?

We now turn to the question if hiring these bankers allows banks to establish long-lasting relationships to borrowers, or if hiring bankers with a portfolio of clients leads to one-off deals.

- Table 8 -

In Table 8 we therefore examine whether the increase in deal volume is due to repeat business with the new clients or if it is a one-time boost. To answer this question we split separately examine the deal volume that a bank has with its clients into the first deal with

[12]Clearly, our results do not exclude the possibility that the SEO and M&A business is influenced by relationships with *investment* bankers. We are arguing that bankers that work in the syndicated lending division of banks have no influence in facilitating the former type of deals.

a firm (*First Deal*), and the deal volume attributable to subsequent deals (*Repeat Deals*). If the boost in observed deal volume where to be due to a one-time interaction, we would find a significant effect only in the case of first deals, and not in subsequent years.

Comparing columns (1) and (4) highlights that this is not the case. Coefficient estimates for all measures of relationships are statistically and economically significant for both first- and subsequent deals. If anything, the banks profit mostly from repeated interactions with the clients for whom they acquire personal relationships.[13] This holds even if we restrict the treatment identifier to the first 5 years after a personal relationship has been acquired as shown in columns (2) and (5). Only when we solely use the first deal that the banks sign with personal relationship clients is the first-deal-effect larger than the repeat-deal-effect. Therefore, it seems that when banks acquire personal relationships to firms they experience a long-lasting boost in deal volume with these companies. Let's think about the "rel_acq_abs" variable here. How is this coefficient identified? isn't it impossible to have repeat deals for which $per_rel_acq_abs$ is 1 by construction?

3.2.5 Exploiting exogenous variation in banker turnover from changes in salary levels

In this section, we exploit a plausibly exogenous variation to the composition of bank's pool of bankers as a shock to their personal relationships to borrowers. One of the major reasons why employees change firms is lack of compensation, and this connection is particularly strong in the financial sector cite anecdotal or papers? . We therefore hypothesize that bankers which are underpaid relative to their peers are more likely to leave their employers, and switch to banks that are paying more attractive salaries. One concern with salary changes is that salaries are tied to individual performance. Bankers with weak performance, for example, might be more likely to get paid less and at the same time leave their employer. We therefore exploit the fact that bonus payments in banking consist of two components:

[13]For brevity we report only the results from our most stringent econometric specification.

a bank-wide performance component, as well as an individual component. Banks allocate bonuses from a general bonus pool. If the bank performs well, the bonus pool is larger and all employees benefit from higher payments. If the bonus pool is smaller, all employees, irrespective of performance, have to accept smaller bonuses. cite anecdotal or papers?

While there is no data on the specific compensation of individual employees, we can proxy for the bank-wide portion of salaries by observing the compensation of board members. We argue that , when bank performance goes down, salaries decrease across the entire bank, leading to a exodus of commercial bankers. Importantly, commercial lending is often only a minor part of bank's profits, and hence a drop in overall bank wide profits is unlikely to be related to the performance of the commercial lending unit. cite saidi neuman 2020 they make similar argument for mergers?

We estimate a 2SLS model on the bank-year level. In the first stage, we estimate the impact of high bank level salaries, measured as the % of salaries above the median, on the bank's ability to attract additional bankers. The outcome variable is therefore ΣRel_acq, the total number of relationships acquired. In the second stage, we estimate the effect of the instrumented number of relationships acquired on the likelihood of initiating new lending relationships. The results are presented in Table 9.

- Table 9 -

Column one shows that paying above the industry median allows banks to attract significantly more bankers. The coefficient estimate of % *Comp above median* on ΣRel_acq is 3.64, and statistically significant at the 5% level. Paying above median slaaries therefore helps banks attract more bankers, which suggests that the instrument fulfills the relevancy criterion. The Kleibergen-Paap F statistic for the first stage is 8.04, which is above the critical Stock and Yogo level, alleviating concerns of a weak instrument. A bank paying 10% above the median in any given year therefore gains about 35 new connections to borrowers, which corresponds to hiring about 8 additional bankers. The second stage results, in column (2), show that when we instrument personal relationship acquisitions in this manner, we find the same relationship between personal relationship acquisition and the initiation of new lending relationships: The coefficient estimate on the instrumented $\Sigma Rel_a cq$ is 4.72, and statistically significant at the 5% level. Can we check the magnitudes here? My interpretation would be that for every relationship acquired, you gain 4.7 initiations? That cannot possibly be correct, right? Do we have to divide by 100? I will just stop writing here, feels like this result might not survive.

Clearly when we write it like this it's a problem. Some ideas: 1. can we maybe plot total board compensation over time and show it is higher during booms and lower during recessions (to substantiate our claim that compensation falls irrespective of performance?) 2. can we try to address the bank issue? I seem to remember that bank FE result in too little variation left over to run our estimation. Is that also true for the quartiles? Is it true if we use executive compensation rather than all board members? Maybe using the Option value of compensation in combination with only executives and quartiles? 3. Alternatively, if it really doesn't work, we can at least proxy for bank size by controling for total number of clients the bank has (either continously or as quantiles? that won't hold up to too much scrutiny but a favorable ref might like it.)

3.2.6 Gender as a friction linking labor and capital markets

In this section, we investigate one particular friction that potentially spills over form bankers' labor markets to corporate loan markets, namely the way corporate culture towards gender impacts female bankers and their clients. The financial industry is often accused of being a particularly hostile work environment for women (**?**), and the gender pay gap in financial services is larger than in most industries (Bureau of Labor Statistics, 2019). We hypothesize that frictions int he labor market from work environment unfriendly to female bankers will induce them to switch employers, and lead to a shift in lenders for their clients. CH: stupid question: are our $discrimination_{t-1}$ variables defined only for those bankers that switch employers? That would induce mechanical relationships, right? Because it is only defined for those that switch? But then we would not be able to estimate this model at all bc there would be a 1-1 mapping between that variable and leaving? Sorry I am confused I am really tired right now. Let's think it through together?

We employ two separate proxies for each bank's climate towards female bankers. Our first proxy builds on prior studies that have shown that female directors improve the climate for female employees (Bilimoria, 2006). We therefore measure the representation of women on each bank's board of directors as a measure of female friendly culture, and define the indicator $No\ female\ director_{t-1}$ to mark those bankers who worked, in the previous year, at an employer without female board members.

Next, we obtain data on labor lawsuits form a non profit organization, the *Good Jobs First* initiative.[14] We then create two indicator variables measuring bank's lawsuit propensity. First, *Empl. discrimination*$_{t-1}$, an indicator that takes the value one for each bank against which at least one general employment discrimination lawsuits was brought in the past. These include lawsuits for discrimination based on age, disability, religion, national origin, and sexual orientation. Second, *Gender discrimination*, a more focused indicator of whether a banks has been the target of a gender discrimination lawsuit, including lawsuits on sexual harassment, pregnancy and gender discrimination.

Table 10 presents results of regressions of our measure *Banker hired*, an indicator in the first year that a banker moves to a new bank, on our measures of female friendly climate interacted with an indicator if a banker is female. All regressions include fixed effects controlling for each bankers old and new banks. We control for time varying propensity to move banks using year fixed effects. Columns 2 and 4 feature additional controls for banker tenure, number of clients and deals, and total number of lawsuits by bank.

- Table 10 -

In columns 1 and 2 of Table 11, we estimate the impact of female board representation on

[14] Available at https://www.goodjobsfirst.org/sites/default/files/docs/pdfs/BigBusinessBias.pdf

the likelihood of female bankers switching to new employers. Consistent with a lack of female board members being the result of, or creating, a less supportive environment for female bankers, we find that the coefficient estimate on the interaction of $Female\ director_{t-1} \times Female$ is 3.54,and significant at the 5% level. These results imply that female bankers were more likely to leave banks with smalelr female board representation.

In column 3, we investigate whether gender discrimination lawsuits have an impact on female bankers. We indeed find that the coefficient on $Genderdiscrimination_{t-1} \times Female$ is 4.95, and statistically significant at the 5% level. Female bankers are therefore almost 5% more likely to leave a bank facing gender discrimination lawsuits as are their male colleagues. This is a sizable effect that represents a three-fold increase compared to the sample mean. This result stays economically and statistically almost unchanged when we add additional banker level controls in column 4.

In column 5, we run a placebo test that investigates if *general* labor lawsuits that are not gender discrimination related have a disproportionate effect on female bankers. Indeed, the interaction term $Empl.\ discrimination_{t-1} \times Female$, is negative and not statistically significant. Female bankers are therefore not more likely than their male counterparts to leave banks faced with general labor lawsuits - they only react differently for specific lawsuits related to gender discrimination.

These results underscore that the climate for female employees at banks can induce significant shifts in the workforce of bankers. In our next set of tests, we investigate if this friction of work place culture spills over into capital market. Specifically, we investigate if female bankers are able to transfer bank-borrower relationships for their clients to their new employer to the same degree as their male colleagues. We therefore repeat the analysis of Table 4 and add an interaction term between Rel_acq and Female that captures whether female bankers exhibit a differential propensity to move clients to new employers.

- Table 11 -

In Table 11 we find that, across all specifications and variations of the definition of

Relationship acquisition, the coefficient estimate on this interaction term is positive and statistically significant, implying that female bankers are at least as likely as their male counterparts to move clients with them to new banks.

In our final result, we investigate if there is a difference in the performance of female bankers relative to their male colleagues depending on the culture of their employer. a large literature in labor economics cite? finds that performance of female bankers suffers in the presence of a less female friendly work environment. In Table 12 we investigate if a similar pattern holds in our sample. We estimate the models from Table 11 for the entire sample, and separately for the sample of banks with- and without gender discrimination lawsuits.

- Table 12 -

The results suggest that female bankers are significantly more productive in the work environment of banks that are not subject to gender discrimination lawsuits both for initiating new banking relationships and generating deal volume. This evidence is consistent with a link between the work environment and performance. Overall, the results in this section support the idea that frictions in the labor market for commercial bankers spill over into the formation of new banking relationships in the capital market.

4 Conclusion

Lending relationships are a key source of capital to the economy, and the lending relationships formed with banks deeply impact borrowers. While the importance of these relationships is well understood, our paper sheds light on one specific mechanisms through which the matching between firms and banks occurs. We use a novel dataset that identifies individual bankers and follows them through time and across banks. We are thus able to show (1) which factors influence banker turnover and crucially (2) whether the personal relationships that banks acquire by employing new bankers translate into new business opportunities.

As for (1), we find that bankers with client portfolios that are more valuable are more likely to switch to a new bank, consistent with the idea that banks recognize the ability of bankers to bring new business. A one standard deviation increase in the number of clients in a banker's portfolio (4.29) increases the chance that this banker switches to a competing bank 40% compared to the unconditional probability. Intuitively, some client relationships are more valuable than others. Consistent with this, we find that large clients, i.e., those that are likely to generate more business, and single-contact clients, i.e., those that are more likely to have a strong relationship with the banker, play a particularly important role in determining the turnover probability of bankers.

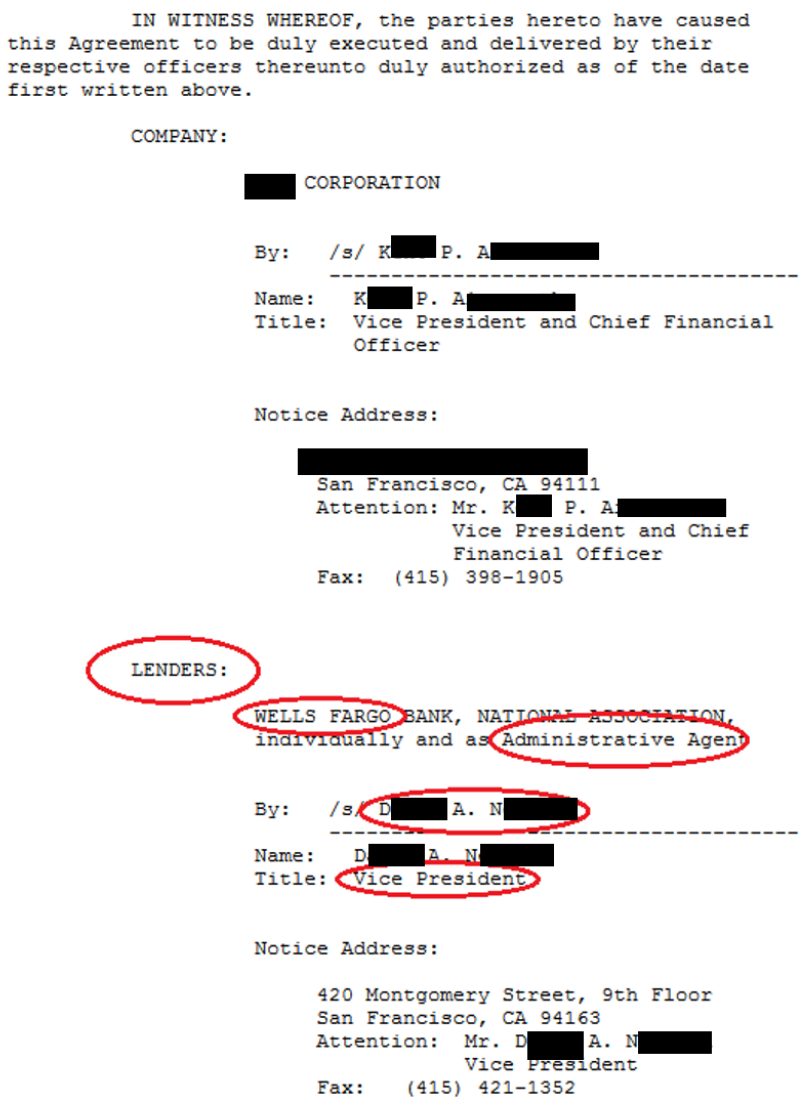
We find strong support for (2): First, when banks acquire a personal relationship to a client by scooping a banker, they increase they substantially increase the likelihood of initiating a new business relation with this firm. Second, these new relationships are accountable for a boost in deal volume compared not only to the banks' existing clients but also relative to new relationships that the bank might form without having a personal contact. Finally, the additional deal volume we document extends beyond syndicated lending to cover bond underwriting and the effect is long lasting.

Having established the importance of individual bankers in shaping banking relationships, we document that frictions from the labor market of corporate bankers spill over into the capital market for borrowers. Specifically, we show that female bankers switch between lenders in a predictable fashion, leaving banks with less female friendly work environments for other banks, in which they subsequently outperform. In the process, these bankers lead to a re-arranging of lending relationships for their borrowers.

Taken together our results show that there are important interactions between the labor market of individual bankers and the bank lending market. Our results highlight the importance of bankers in enabling the formation of banking relationships and uncover the bankers' characteristics that are material to explain banker turnover. Future work could identify other types of labor market frictions, and further identify the effects of these frictions on borrower performance and loan outcomes.

Figures

Figure 3: Example of simple signature page with a single bank
The red circles indicate information extracted by the text search algorithm. This information includes the name and role of the bank, as well as the name and title of the signatory. The names of the banker, corporation, and corporate executive are anonymized for the sake of privacy. The prior literature offers additional, detailed descriptions of the data, as well as extensive quality checks (e.g. Herpfer, 2018; Bushman et al., 2019).



IN WITNESS WHEREOF, the parties hereto have caused this Agreement to be duly executed and delivered by their respective officers thereunto duly authorized as of the date first written above.

COMPANY:

[redacted] CORPORATION

By: /s/ K[redacted] P. A[redacted]

Name: K[redacted] P. A[redacted]
Title: Vice President and Chief Financial Officer

Notice Address:

[redacted]
San Francisco, CA 94111
Attention: Mr. K[redacted] P. A[redacted]
Vice President and Chief Financial Officer
Fax: (415) 398-1905

LENDERS:

WELLS FARGO BANK, NATIONAL ASSOCIATION,
individually and as Administrative Agent

By: /s/ D[redacted] A. N[redacted]

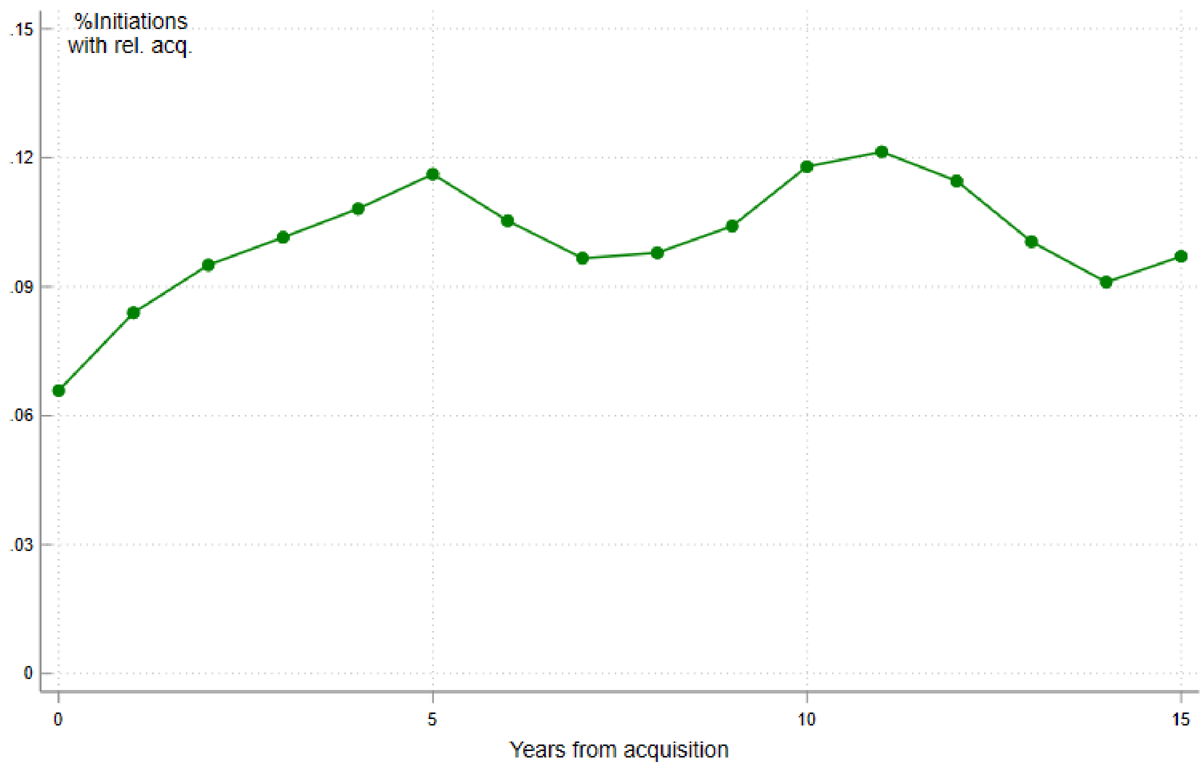
Name: D[redacted] A. N[redacted]
Title: Vice President

Notice Address:

420 Montgomery Street, 9th Floor
San Francisco, CA 94163
Attention: Mr. D[redacted] A. N[redacted]
Vice President
Fax: (415) 421-1352

Figure 4: Active bankers over time
The figure shows the total number of active bankers in the sample (red line) and the cumulative number of bankers that switched and are still active (green line). Bankers are considered active for all years between the first and last deal they sign.

Figure 5: Relationships acquired and initiations over time
The figure shows the average yearly percentage of clients with whom a bank initiates a business relationship and for whom a personal relationship has been acquired. The x-axis show the number of years that elapsed since acquiring the relationship. CH: I am so sorry to keep pestering you about this graph but it still is not looking the way I have it in my head (and I am really stubborn :)). This line should never go down. Right now, I understand the line some times goes down because some bankers are leaving the sample. I do not think that should happen if the data is constructed the way I think it is? Say we have some observations that took the value "initiation = 1, rel_acq = 1". then the banker leaves the sample because she was inactive for 5 years (right? this is why the line only ever drops after 5 years?) But then initiation =1 and rel_acq = 0?



Tables

Table 1: Summary statistics - Bankers' personal relationships
This table shows summary statistics of the sample variables relating to bankers' personal relationships. The sample in Panel A is at the banker-year level while in Panel B it is at the bank-year level. All Panels cover the years from 1996 to 2013. The bankers' employment information and their client portfolio is retrieved from EDGAR. Firms' balance sheet information is from Compustat. Variables are defined as in Appendix Table A1.

Panel A: Client portfolios of bankers

	N	p25	mean	p50	p75	sd
Banker hired (%)	66,774	0.00	1.57	0.00	0.00	12.42
Banker female (%)	58,663	0.00	18.91	0.00	0.00	39.16
Tenure (yrs.)	66,774	1.00	3.72	3.00	5.00	3.13
#Clients - Total	66,774	1.00	3.07	2.00	3.00	4.29
#Clients - Small	66,774	0.00	0.08	0.00	0.00	0.33
#Clients - Large	66,774	0.00	1.50	1.00	2.00	3.00
#Clients - Single contact	66,774	0.00	1.48	1.00	2.00	2.37
#Clients - Mult. contact	66,774	0.00	1.58	1.00	2.00	2.80
#Deals - Total	66,774	1.00	4.14	2.00	5.00	6.36
#Deals - Small	66,774	0.00	0.11	0.00	0.00	0.52
#Deals - Large	66,774	0.00	1.97	1.00	2.00	4.40
#Deals - Mult. contact	66,774	0.00	1.97	1.00	2.00	4.25
#Deals - Single contact	66,774	1.00	2.51	1.00	3.00	4.14

Panel B: Bank-level summary statistics

	N	p25	mean	p50	p75	sd
#Bankers employed	12,959	1.00	16.00	3.00	9.00	49.55
Mean deals per banker-yr	12,964	1.00	1.46	1.00	2.00	2.03
#Clients - Total	12,937	2.00	28.91	6.00	18.00	82.48
#Clients - Small	12,964	0.00	0.32	0.00	0.00	0.79
#Clients - Large	12,964	0.50	2.73	1.00	3.00	4.47
#Clients - Mult. bankers	12,964	0.00	0.25	0.00	0.00	0.43
Discrimination lawsuit	12,964	0.00	0.03	0.00	0.00	0.16

Table 2: Summary statistics - Banks' client portfolio

This table shows summary statistics of the sample variables relating to the banks' client portfolio The sample is at the bank-borrower-year level and covers the years from 1996 to 2013. Panel A shows all bank-firm pairs, while Panel B shows deal volume conditional on signing at least one deal for a given bank-borrower-year. Panel C shows summary statistics at the firm-year level. The bankers' employment information and their client portfolio is retrieved from EDGAR. Bond ans SEO underwriting as well as M&A advisory deals are retrieved from CapitalIQ. Syndicated loans are from Dealscan. Balance sheet information is from Compustat. Variables are defined as in Appendix Table A1.

Panel A: All bank-firm pairs

	N	p25	mean	p50	p75	sd
Rel_acq (%)	972,090	0.00	2.93	0.00	0.00	16.86
Rel_acq^{5yr} (%)	958,299	0.00	1.53	0.00	0.00	12.28
Rel_acq^{abs} (%)	946,214	0.00	0.27	0.00	0.00	5.23
Rel_acq_nofirst (%)	969,584	0.00	2.68	0.00	0.00	16.14
Rel_acq_nofirst^{5yr} (%)	955,796	0.00	1.27	0.00	0.00	11.22
Rel_acq_nofirst^{abs} (%)	946,311	0.00	0.28	0.00	0.00	5.33
Initiation (%)	972,090	0.00	5.20	0.00	0.00	22.19

Panel B: All bank-firm pairs, conditional on signing at least one deal

	N	p25	mean	p50	p75	sd
Volume - All deals	89,066	100.00	827.93	276.45	718.11	2,543.72
Volume - Synd. Loans	89,066	0.00	417.48	25.00	300.00	1,571.22
Volume - Bonds	89,066	0.00	279.48	0.00	185.32	1,215.99
Volume - SEOs	89,066	0.00	56.23	0.00	0.00	459.01
Volume - M&As	89,066	0.00	74.74	0.00	0.00	1,281.47
#Deals - Total	89,066	1.00	1.74	1.00	1.00	17.43
#Delas - Synd. loans	89,066	0.00	0.64	1.00	1.00	0.75
#Delas - Bonds	89,066	0.00	0.81	0.00	1.00	17.45
#Delas - SEOs	89,066	0.00	0.17	0.00	0.00	0.45
#Delas - M&A	89,066	0.00	0.04	0.00	0.00	0.21

Panel C: Firm-level variables

	N	p25	mean	p50	p75	sd
Total Assets	78,401	179.19	6,922.45	731.36	3,106.57	26,354.11
Leverage	77,547	0.38	0.57	0.56	0.73	0.29
EBITDA	74,450	5.20	226.95	32.97	133.74	771.83
Profitability	72,453	0.02	0.05	0.04	0.11	0.15
Intangibles to Assets	64,579	0.00	0.14	0.05	0.22	0.19

Table 3: Bankers' switching and size of client portfolio
This table shows regressions of an indicator value (in %) for the first year a banker appears at a new bank on the lagged client portfolio characteristics of the banker. In Panel A these are the number of clients and in Panel B the number of deals that the banker signs with her client portfolio at the bank. Columns (3) and (4) show the portfolio characteristics by clients' size. Columns (5) and (6) explore the trade off between the quantity and quality of the client portfolio by treating the single contact and multiple contact clients separately. The sample covers all banker-years pairs between 1996 and 2013. Variables are defined as in Appendix Table A1. t-statistics, based on robust standard errors clustered two dimensionally at lender and bank level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Panel A: Number of clients

Dep. variable:	Banker hired (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
#Clients - Total$_{t-1}$	0.21***	0.15***				
	(4.42)	(3.87)				
#Clients - Small$_{t-1}$			0.63**	0.34		
			(2.02)	(1.07)		
#Clients - Large$_{t-1}$			0.25***	0.17***		
			(4.04)	(3.43)		
#Clients - Single contact$_{t-1}$					0.46***	0.58***
					(3.67)	(4.14)
#Clients - Mult. contact$_{t-1}$					0.02	-0.14**
					(0.25)	(-2.10)
Observations	46,075	39,992	46,075	39,992	46,075	39,992
R-squared	0.11	0.21	0.11	0.21	0.11	0.22
Bank and Year FE	Yes	No	Yes	No	Yes	No
Bank × Year FE	No	Yes	No	Yes	No	Yes

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Panel B: Number of deals

Dep. variable:	Banker hired (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Total #Deals$_{t-1}$	0.14***	0.10***				
	(4.66)	(4.05)				
#Deals - Small$_{t-1}$			0.38**	0.18		
			(2.02)	(1.10)		
#Deals - Large$_{t-1}$			0.16***	0.11***		
			(3.99)	(3.35)		
#Deals - Single contact$_{t-1}$					0.08**	0.11***
					(2.19)	(2.79)
#Deals - Mult. contact$_{t-1}$					0.06	-0.02
					(1.29)	(-0.52)
Observations	46,075	39,992	46,075	39,992	46,075	39,992
R-squared	0.11	0.21	0.11	0.21	0.11	0.21
Bank and Year FE	Yes	No	Yes	No	Yes	No
Bank × Year FE	No	Yes	No	Yes	No	Yes

Table 4: Initiation

This table shows regressions of an indicator for a new bank-borrower relationships on an indicator for personal relationship acquired, which identifies deals with the old clients of bankers that switch employers. In columns (1) to (4), the indicator variable takes the value of one for all years after the banker switches. In (5) and (6) it is set to missing after 5 and 1 year respectively. The dependent variable is an indicator for bank-borrower relationships that are new or for whom the bank had no interaction in the past 5 years. The sample is at the bank-borrower-year level and spans from 1996 to 2013. Bond and SEO underwriting as well as M&A advisory deals are retrieved from CapitalIQ. Syndicated loans are from Dealscan. Variables are defined as in Appendix Table A1. t-statistics, based on robust standard errors clustered two dimensionally at firm and lender level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Dep. variable:	Initiation					
	(1)	(2)	(3)	(4)	(5)	(6)
Rel_acq	0.07**	0.09**	0.13***	0.14***		
	(2.37)	(2.38)	(3.58)	(3.80)		
Rel_acq^{5yr}					0.12***	
					(3.54)	
Rel_acq^{abs}						0.07***
						(3.34)
Observations	861,444	861,444	861,444	861,444	847,102	834,461
R-squared	0.03	0.08	0.10	0.42	0.41	0.41
Year FE	Yes	Yes	Yes	No	No	No
Firm FE	Yes	No	No	No	No	No
Bank FE	Yes	No	No	No	No	No
Firm-Bank FE	No	Yes	Yes	Yes	Yes	Yes
Bank-Year FE	No	No	Yes	Yes	Yes	Yes
Firm-Year FE	No	No	No	Yes	Yes	Yes

Table 5: Initiation - Opaque clients

This table shows regressions of XXX Variables are defined as in Appendix Table A1. t-statistics, based on robust standard errors clustered at firm and lender level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Dep. variable:	Initiation		
	(1)	(2)	(3)
Rel_acq × Junk	0.16***		
	(3.82)		
Junk	0.01*		
	(1.85)		
Rel_acq	0.22***		
	(3.77)		
Rel_acq × Hi Intang		0.19***	
		(3.63)	
Hi Intang		0.02***	
		(3.91)	
Rel_acq		0.16***	
		(3.43)	
Rel_acq × Small			0.07***
			(3.76)
Small			-0.01***
			(-2.95)
Rel_acq			0.15***
			(3.49)
Observations	203,874	355,856	434,134
R-squared	0.22	0.16	0.15
Year FE	Yes	Yes	Yes
Firm-Bank FE	Yes	Yes	Yes
Bank-Year FE	Yes	Yes	Yes

Table 6: Total deal volume

This table shows regressions of the logarithm of total deal volume on an indicator for personal relationship acquired, which identifies deals with the old clients of bankers that switch employers. The indicator variable takes the value of one for all years after the banker switches in columns (1) to (4) while in (5) and (6) it is set to missing after 5 and 1 year respectively. Panel B adds the interaction terms with an indicator for bank-borrower relationships that are new or for whom the bank had no interaction in the past 5 years. Firms for which a relationship is acquired but never close a deal with the bank are dropped. The sample is at the bank-borrower-year level and spans from 1996 to 2013. Bond and SEO underwriting as well as M&A advisory deals are retrieved from CapitalIQ. Syndicated loans are from Dealscan. Variables are defined as in Appendix Table A1. t-statistics, based on robust standard errors clustered two dimensionally at firm and lender level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Panel A: Relationship acquired

Dep. variable:	Log Deal Volume					
	(1)	(2)	(3)	(4)	(5)	(6)
Rel_acq	0.66***	0.72***	0.62***	0.35***		
	(6.78)	(3.79)	(4.58)	(3.85)		
Rel_acq^{5yr}					0.37***	
					(3.82)	
Rel_acq^{abs}						2.34***
						(6.20)
Observations	809,173	809,173	809,173	809,173	807,720	806,190
R-squared	0.07	0.14	0.16	0.51	0.51	0.51
Year FE	Yes	Yes	Yes	No	No	No
Firm FE	Yes	No	No	No	No	No
Firm-Bank FE	No	Yes	Yes	Yes	Yes	Yes
Bank-Year FE	No	No	Yes	Yes	Yes	Yes
Firm-Year FE	No	No	No	Yes	Yes	Yes

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Panel B: Interaction with initiation

Dep. variable:	Log Deal Volume					
	(1)	(2)	(3)	(4)	(5)	(6)
Rel_acq × Initiation	1.64***	1.58***	1.53***	1.21***		
	(14.37)	(8.44)	(10.11)	(11.11)		
Rel_acq	-0.29***	-0.43***	-0.45***	-0.42***		
	(-4.91)	(-2.69)	(-3.14)	(-3.96)		
Initiation	4.91***	4.84***	4.81***	4.55***		
	(64.61)	(63.95)	(61.92)	(95.03)		
Rel_acq^{5yr} × Initiation					1.37***	
					(11.22)	
Rel_acq^{5yr}					-0.38***	
					(-3.59)	
Initiation					4.55***	
					(96.22)	
Rel_acq^{abs} × Initiation						3.52***
						(8.96)
Rel_acq^{abs}						0.88**
						(2.01)
Initiation						4.56***
						(98.81)
Observations	921,504	921,504	921,504	809,173	807,720	806,190
R-squared	0.53	0.57	0.58	0.73	0.73	0.74
Year FE	Yes	Yes	Yes	No	No	No
Firm FE	Yes	No	No	No	No	No
Firm-Bank FE	No	Yes	Yes	Yes	Yes	Yes
Bank-Year FE	No	No	Yes	Yes	Yes	Yes
Firm-Year FE	No	No	No	Yes	Yes	Yes

Table 7: Total deal volume by category

This table shows regressions of the logarithm of total deal volume by category on an indicator for personal relationship acquired, which identifies deals with the old clients of bankers that switch employers. The indicator variable takes the value of one for all years after the banker switches in columns (1) to (4) while in (5) and (6) it is set to missing after 5 and 1 year respectively. The dependent variable in Panel A is syndicated loans volume, in Panel B bond underwriting, and in Panel C seasoned equity offerings (SEOs). Firms for which a relationship is acquired but never close a deal with the bank are dropped. The sample covers respectively all bank-borrower-year observations where there is at least one syndicated loan, bond, or SEO per bank-borrower-year. In all panels, the sample spans from 1996 to 2013. Bond ans SEO underwriting as well as M&A advisory deals are retrieved from CapitalIQ. Syndicated loans are from Dealscan. Variables are defined as in Appendix Table A1. t-statistics, based on robust standard errors clustered two dimensionally at firm and lender level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Panel A: Syndicated loans

Dep. variable:	Log Deal Volume - Syndicated Loans					
	(1)	(2)	(3)	(4)	(5)	(6)
Rel_acq	0.22***	0.08	0.08	0.18**		
	(4.08)	(0.92)	(0.96)	(1.99)		
Rel_acq^{5yr}					0.22**	
					(2.18)	
Rel_acq^{abs}						1.66***
						(4.31)
Observations	789,165	789,165	789,165	789,165	787,804	786,402
R-squared	0.07	0.17	0.19	0.49	0.49	0.49
Year FE	Yes	Yes	Yes	No	No	No
Firm FE	Yes	No	No	No	No	No
Firm-Bank FE	No	Yes	Yes	Yes	Yes	Yes
Bank-Year FE	No	No	Yes	Yes	Yes	Yes
Firm-Year FE	No	No	No	Yes	Yes	Yes

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Panel B: Bond underwriting

Dep. variable:	Log Deal Volume - Bonds					
	(1)	(2)	(3)	(4)	(5)	(6)
Rel_acq	0.59***	0.81***	0.71***	0.24***		
	(6.19)	(7.49)	(8.89)	(3.05)		
Rel_acq^{5yr}					0.23**	
					(2.36)	
Rel_acq^{abs}						1.59***
						(3.55)
Observations	771,283	771,283	771,283	771,283	769,815	768,275
R-squared	0.13	0.20	0.21	0.59	0.59	0.58
Year FE	Yes	Yes	Yes	No	No	No
Firm FE	Yes	No	No	No	No	No
Firm-Bank FE	No	Yes	Yes	Yes	Yes	Yes
Bank-Year FE	No	No	Yes	Yes	Yes	Yes
Firm-Year FE	No	No	No	Yes	Yes	Yes

Panel C: SEO underwriting

Dep. variable:	Log Deal Volume - SEOs					
	(1)	(2)	(3)	(4)	(5)	(6)
Rel_acq	0.07	0.05	0.02	0.04		
	(1.54)	(0.52)	(0.22)	(0.62)		
Rel_acq^{5yr}					0.03	
					(0.52)	
Rel_acq^{abs}						0.30
						(1.00)
Observations	757,528	757,528	757,528	757,528	756,272	754,935
R-squared	0.07	0.12	0.13	0.57	0.57	0.57
Year FE	Yes	Yes	Yes	No	No	No
Firm FE	Yes	No	No	No	No	No
Firm-Bank FE	No	Yes	Yes	Yes	Yes	Yes
Bank-Year FE	No	No	Yes	Yes	Yes	Yes
Firm-Year FE	No	No	No	Yes	Yes	Yes

Table 8: Deal volume - First deal vs. Repeat deals

This table shows regressions of the logarithm of total deal volume on an indicator for personal relationship acquired, which identifies deals with the old clients of bankers that switch employers. The indicator variable takes the value of one for all years after the banker switches in columns (1) and (4), in (2) and (5) it is set to missing after 5 years, and in (3) and (6) it set to missing after 1 year. The dependent variable in the first three columns is the volume of the first deal that a banker does with one of her old clients after switching to the new bank. The dependent variable in the last three columns is the volume of deals that come from repeated interactions with old clients (excluding the first one). The sample covers respectively all bank-borrower-year observations where there is either no deal or at least one syndicated loan, bond, or SEO per bank-borrower-year. The sample spans from 1996 to 2013. Bond ans SEO underwriting as well as M&A advisory deals are retrieved from CapitalIQ. Syndicated loans are from Dealscan. Variables are defined as in Appendix Table A1. t-statistics, based on robust standard errors clustered two dimensionally at firm and lender level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Dep. variable:	Log Volume - First deal			Log Volume - Repeat deals		
	(1)	(2)	(3)	(4)	(5)	(6)
Rel_acq	0.86***			1.40***		
	(12.50)			(13.37)		
Rel_acq^{5yr}		0.99***			1.24***	
		(13.39)			(9.52)	
Rel_acq^{abs}			4.71***			1.69***
			(11.71)			(6.17)
Observations	818,718	817,203	815,622	818,718	817,203	815,622
R-squared	0.26	0.30	0.84	0.43	0.40	0.42
Firm-Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Decrease in board's salary as an instrument for bankers' switching
This table shows 2SLS-regressions of the total number of initiations and deal volume that a bank closes during a year on the sum of relationships acquired. For each year we compute the salary that a bank's board members receive above the sample median. We use this lagged variable as an instrument for the number of relationships a bank acquires in columns (1), (2), (5), and (6). We use quartiles in (3) and (4). The sample spans from 1996 to 2013 and is at the bank-year level. It contains only banks for which board compensation data is available. Variables are defined as in Appendix Table A1. t-statistics, based on robust standard errors clustered two dimensionally at the year and bank level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Dep. variable:	ΣInitiation				ΣLog Deal Volume	
	(1)	(2)	(3)	(4)	(5)	(6)
ΣRel_acq		4.72**		3.47***		0.04**
		(2.84)		(3.53)		(2.53)
%Comp Above Med	3.64**				4.24**	
	(1.98)				(2.27)	
%Comp Above Med - Qrt=2			7.85			
			(1.52)			
%Comp Above Med - Qrt=3			15.85**			
			(2.41)			
%Comp Above Med - Qrt=4			31.14***			
			(3.02)			
F-statistic for IV in first stage		8.04		12.46		6.42
Observations	722	722	786	786	517	517
Year FE		Yes		Yes		Yes

Table 10: Spillovers of frictions from labor to capital markets: gender
This table shows regressions of an indicator value (in %) for the first period after a bank hired a banker on measures of corporate culture towards female bankers and their interaction with an indicator whether a banker is Female. *Empl. discrimination*$_{t-1}$ and *Gender discrimination*$_{t-1}$ are indicators if the last employer of the banker has been the subject of a general employment or gender discrimination lawsuit, respectively. *No Female director*$_{t-1}$ is an indicator for the absence of female directors at the last employer of the banker. The sample is at the bank-banker-year level and spans 1996 to 2013. Variables are defined as in Appendix Table A1. t-statistics, based on robust standard errors clustered at lender and banker level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	Board		Lawsuits		Placebo
	(1)	(2)	(3)	(4)	(5)
No Female director$_{t-1}$ × Female	3.54**	2.82*			
	(-2.38)	(-1.98)			
No Female director$_{t-1}$	0.14	0.71			
	(-0.16)	(-0.75)			
Gender discrimination$_{t-1}$ × Female			4.49**	4.54**	
			(2.26)	(2.00)	
Gender discrimination$_{t-1}$			-16.80	-17.17	
			(-1.12)	(-1.16)	
Other lawsuits$_{t-1}$ × Female					-3.19
					(-1.21)
Other lawsuits$_{t-1}$					-15.39
					(-0.97)
Female	4.20*	4.25**	0.62	0.73	2.15
	(1.83)	(2.45)	(0.40)	(0.46)	(1.52)
Observations	552	552	3,308	3,308	3,308
R-squared	0.94	0.94	0.86	0.86	0.86
Prev. Bank FE	Yes	Yes	Yes	Yes	Yes
Bank and Year FE	Yes	Yes	Yes	Yes	Yes
Banker controls	No	Yes	No	Yes	No

Table 11: Initiation - Female bankers

This table shows regressions of an indicator for a new bank-borrower relationships on an indicator for personal relationship acquired, which identifies deals with the old clients of bankers that switch employers. In columns (1) to (4), the indicator variable takes the value of one for all years after the banker switches. In (5) and (6) it is set to missing after 5 and 1 year respectively. The dependent variable is an indicator for bank-borrower relationships that are new or for whom the bank had no interaction in the past 5 years. The sample is at the bank-borrower-year level and spans 1996 to 2013. Variables are defined as in Appendix Table A1. t-statistics, based on robust standard errors clustered at firm and lender level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Dep. variable:	Initiation					
	(1)	(2)	(3)	(4)	(5)	(6)
Rel_acq	0.07**	0.09**	0.13***	0.14***		
	(2.39)	(2.40)	(3.57)	(3.83)		
Rel_acq × Female	0.07*	0.06*	0.11***	0.10***		
	(1.76)	(1.81)	(3.22)	(2.95)		
Rel_acq^{5yr}					0.13***	
					(3.56)	
Rel_acq^{5yr} × Female					0.09***	
					(2.82)	
Rel_acq^{abs}						0.07***
						(3.41)
Rel_acq^{abs} × Female						0.06*
						(1.70)
Observations	861,444	861,444	861,444	861,444	847,102	834,461
R-squared	0.03	0.08	0.10	0.42	0.41	0.41
Year FE	Yes	Yes	Yes	No	No	No
Firm FE	Yes	No	No	No	No	No
Firm-Bank FE	No	Yes	Yes	Yes	Yes	Yes
Bank-Year FE	No	No	Yes	Yes	Yes	Yes
Firm-Year FE	No	No	No	Yes	Yes	Yes

Table 12: Initiation and deal volume - Female bankers

This table shows XXX The sample is at the bank-borrower-year level and spans 1996 to 2013. Variables are defined as in Appendix Table A1. t-statistics, based on robust standard errors clustered at firm and lender level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	Initiation			Log Deal Volume		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Lawsuit	No Lawsuit	All	Lawsuit	No Lawsuit
Rel_acq × Female	0.10***	0.28***	0.08***	0.19	-0.40	0.84*
	(2.95)	(3.39)	(2.91)	(0.44)	(-0.76)	(1.85)
Rel_acq	0.14***	0.23**	0.12***	0.36***	0.55*	0.35***
	(3.83)	(2.89)	(3.58)	(3.75)	(2.26)	(3.27)
Observations	861,444	87,372	691,902	809,173	79,918	647,276
R-squared	0.42	0.54	0.43	0.51	0.61	0.53
Firm-Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 13: Probability of switching and non-compete clauses

This table shows regressions of an indicator value (in %) for the first period after a bank hired a banker on an indicator for changes in non-compete laws from (**?**). The indicator is positive for the bankers that live in a state that increases the enforceability of non-competes. Controls include the logarithm of the number of bankers in a given state during a year, the non-compete stringency of the state in 1991 and 2009 (**?**), and year times region fixed effects. The sample includes all banker-years for which the bankers' location has been matched manually (columns (1) and (2)) and through LinkedIn searches (columns (3) and (4)). t-statistics, based on robust standard errors clustered at banker and lender level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Dep. var:	Banker switched (%)			
	Manual Check		LinkedIn	
	(1)	(2)	(3)	(4)
PostXTreated	-1.58***	-2.96***	-1.87***	-2.09***
	(-2.65)	(-3.19)	(-3.62)	(-3.52)
Log #Bankers per state	-0.35	-0.07	-0.10	-0.04
	(-1.09)	(-0.18)	(-0.36)	(-0.12)
NC-Rank 1991		-0.00		0.00
		(-0.03)		(0.07)
NC-Rank 2009		-0.05		-0.01
		(-1.01)		(-0.39)
Observations	2,530	2,525	5,885	5,877
YearXRegion FE	Yes	Yes	Yes	Yes

Appendix for
"How do borrowers find their banks?
The value of individuals in bank relationship formation"

A Anecdotal evidence

This section provides anecdotal evidence of both bankers being actively poached by competing lenders, and their ability to move their clients with them.

1. The following article details how JPMorgan poached commercial bankers from various competitors to bolster its lending business:[15]

   JPMorgan Chase & Co on Wednesday named half a dozen people to a commercial banking team in Europe and new international and Asia-Pacific regional leaders, as the U.S. bank closes in on business clients it hopes to poach from rivals abroad.

2. Smaller lenders follow the same strategy:[16]

   As CEO of Manhattan-based Signature Bank (SBNY), DePaolo recently set out to recruit four teams of veteran bankers from large rivals [...] The strategy gives smaller firms a crack at picking off large rivals' clients, says Jeff Davis, senior analyst at FTN Financial, a unit of First Horizon National Corp. (FHN). That's because ***business customers are notoriously loyal to their bankers.*** *Signature, which has 22 offices in the New York metro area, has virtually raided the ranks of what was once North Fork Bank, a former 350-branch Long Island lender. More than 80 North Fork alumni have moved to Signature since Capital One Financial Corp.*
   Jim Schmitz, president of middle Tennessee for Regions, based in Birmingham, intends to add more Nashville bankers at the beginning of 2013. ***He said he would try to recruit from rival banks if he can find local lenders who can bring "relationships with companies we don't already have. The competition for people and customers is as a fierce as I've ever seen it****," he said.*

3. Banks strategically time their poaching of talent from competitors, for example after a merger:[17]

   The $161 billion-asset Citizens has already recruited one team of commercial bankers away from SunTrust, and its top commercial banker said Tuesday that he expects the merger — the industry's largest in more than a decade — to lead to more banker

[15] Article available at https://www.reuters.com/article/us-jp-morgan-europe/jpmorgan-hires-commercial-bankers-leaders-across-europe-asia-idUSKCN1QG2SQ

[16] Article available at https://www.boyden.com/media/small-regional-banks-find-ease-poaching-large-bank-tal index.html

[17] Article available at https://www.americanbanker.com/news/citizens-looks-to-poach-bb-t-suntrust-talent-bu

defections. ***McCree said Tuesday that Citizens has been adding around 300 new clients every year across its footprint, and it's done so primarily by hiring local bankers in its newer markets. [...] "They are bringing clients with them, which is one of my goals when I hire people", he said.*** *[...] Several banks in the Southeast and mid-Atlantic have said that they intend to go after customers and bankers that might be looking to leave BB&T-SunTrust when that merger closes.*

4. Bankers are aware of their important role in forming relationships to borrowers:[18]

   Bankers often talk about C&I lending as a relationship-driven business*, so an acquisition could force large clients to reconsider their lending partners. Commercial borrowers often select banks for reasons beyond the loan's terms and pricing, valuing institutions that can also deliver cash management, debt syndication or other services.*

5. Banks are aware of the risk of defecting bankers taking clients with them, and strictly enforce cool down periods and non compete agreements:[19]

   The prolific rainmaker received an ***immediate termination from Credit Suisse after the bank accused him of breaking rules governing contact with clients****. The basis of trust between Illy and UBS eroded as a result of the episode, which represents a rare public glimpse into how competitive banks are with their talent.*

6. The following excerpt describes how borrowers moved their banking relationship as bankers switched to a new lender:[20]

   [CEO Dan Ariens] approached his lender, LaSalle Bank, to see if it would ramp up his $30 million credit line to $45 million. But LaSalle, which on Oct. 1 was bought by Bank of America Corp., would never get the additional business. [....] ***Ariens, in fact, ended up moving nearly all of his banking relationships to PrivateBancorp Inc. The Chicago-based bank hired 56 managing directors in the fourth quarter, most of them from LaSalle****, and posted a 12 percent increase in loans compared with the year-ago quarter.* ***"It felt natural to stay with the people we knew,"*** *he said.*

[18] Article available at https://www.spglobal.com/marketintelligence/en/news-insights/research/ma-creates-poaching-opportunities-for-commercial-credits

[19] Article available at https://www.finews.com/news/english-news/34276-marco-illy-ubs-credit-suisse-investment-bank-switzerland-credit-suisse-notice-contract-dissolved

[20] Article available at https://www.chicagotribune.com/news/ct-xpm-2008-02-18-0802170180-story.html

Appendix Tables

Table A1: Variable definitions

Panel A: Bankers' client portfolio

Banker hired	Indicator for the first year that a banker appears at a new bank (not counting the first appearance of the banker in the sample).
#Clients - Total	Running number of clients with whom the banker has at least one deal.
#Clients - Small	Running number of small clients (total assets below 25th percentile for the year) with whom the banker has at least one deal.
#Clients - Large	Running number of large clients (total assets above 75th percentile for the year) with whom the banker has at least one deal.
#Clients - Single contact	Running number of clients for whom the banker is the single contact at the bank.
#Clients - Mult. contact	Running number of clients that sign deals with multiple bankers, for whom the banker has also at least one deal.
#Deals - Total	Running number of deals that a banker signs at a bank.
#Deals - Small	Running number of deals that a banker signs with small clients (total assets below 25th percentile for the year) at a bank.
#Deals - Large	Running number of deals that a banker signs with large clients (total assets above 75th percentile for the year) at a bank.
#Deals - Single contact	Running number of deals with clients for whom the banker is the single contact at the bank.
#Deals - Mult. contact	Running number of deals with clients that sign deals with multiple bankers, for whom the banker has also at least one deal.

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Panel B: Banks' client portfolio

$\text{Initiation}_{i,j,t}$	Indicator for the year t when bank j makes a deal (syndicated loan, bond underwriting, SEOs, or M&A advisory) with firm i for the first time ever or for the first time in more than five years.
$\text{Initiation\_strict}_{i,j,t}$	Indicator for the year t when bank j makes a deal with firm i for the first time.
$\text{Rel\_acq}_{i,j,t}$	Indicator variable for the year t when a bank j makes a deal with firm i for the first time ever or for the first time in five years *and* firm i was in the clinet portfolio of a banker that switched to bank j before time t.
$\text{Rel\_acq}^{5yr}_{i,j,t}$	Same as $\text{Rel\_acq}_{i,j,t}$, but takes the value of 1 also for the years $t+1$ to $t+4$.
$\text{Rel\_acq}^{abs}_{i,j,t}$	Same as $\text{Rel\_acq}_{i,j,t}$, but is set to missing for all years after t.
$\text{Rel\_acq\_nofirst}_{i,j,t}$	Same as $\text{Rel\_acq}_{i,j,t}$, but excludes the first deal of the banker at the new bank.
$\text{Rel\_acq\_nofirst}^{5yr}_{i,j,t}$	Same as $\text{Rel\_acq}^{5yr}_{i,j,t}$, but excludes the first deal of the banker at the new bank.
$\text{Rel\_acq\_nofirst}^{abs}_{i,j,t}$	Same as $\text{Rel\_acq}^{abs}_{i,j,t}$, but excludes the first deal of the banker at the new bank.
Log Deal Value	Logarithm of the total value of deals (in USDmm) that bank j underwrites for firm i in year t, including syndicated loans, bonds, and SEOs.
Log Syndicated loans	Logarithm of the total value of syndicated loans taken out by firm i in year t for which bank j acts as lead arranger.
Log Bonds	Logarithm of the total value of bonds that bank j underwrites for firm i in year t.
Log M&As	Logarithm of the total value of M&A transactions for which bank j acts as adviser for firm i in year t.
Log Volume - First deal	Logarithm of the value of the first deal that a firm signs at a bank.
Log Volume - Repeat deals	Logarithm of the total value of all deals that a firm sings at a bank, except the first.

Table A2: Bankers' switching and distribution of client portfolio
This table shows regressions of an indicator value (in %) for the first year a banker appears at a new bank on the lagged client portfolio characteristics of the banker. In Panel A these are the client distribution and in Panel B the deal distribution within a bank. The sample covers all banker-years pairs between 1996 and 2013. Variables are defined as in Appendix Table A1. t-statistics, based on robust standard errors clustered two dimensionally at lender and bank level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Dep. variable:	Banker hired (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Log rank #clients	-0.01	0.05				
	(-0.17)	(1.06)				
No_clients$^{25\%-50\%}$			-0.13**	-0.12*		
			(-2.06)	(-1.93)		
No_clients$^{50\%-75\%}$			-0.02	0.01		
			(-0.26)	(0.11)		
No_clients$^{75\%-100\%}$			0.06	0.08		
			(0.83)	(1.05)		
Log rank #clients - small					-0.17***	0.09
					(-2.97)	(0.62)
Log rank #clients - large					0.10***	0.14***
					(3.32)	(3.48)
Observations	45,123	39,152	45,123	39,152	45,123	39,152
R-squared	0.06	0.10	0.06	0.10	0.06	0.10
Bank and Year FE	Yes	No	Yes	No	Yes	No
Bank × Year FE	No	Yes	No	Yes	No	Yes

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Panel B: Number of deals

Dep. variable:	Banker hired (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Log rank #deals$_{t-1}$	-0.04	-0.02				
	(-1.26)	(-0.58)				
No_deals$_{t-1}^{25\%-50\%}$			-0.11*	-0.12*		
			(-1.81)	(-1.72)		
No_deals$_{t-1}^{50\%-75\%}$			-0.03	0.00		
			(-0.47)	(0.06)		
No_deals$_{t-1}^{75\%-100\%}$			0.00	0.03		
			(0.04)	(0.40)		
Log rank #deals - small$_{t-1}$					0.02	0.05***
					(0.84)	(2.60)
Log rank #deals - large$_{t-1}$					0.01	0.05*
					(0.56)	(1.87)
Observations	45,123	39,152	45,123	39,152	45,123	39,152
R-squared	0.06	0.10	0.06	0.10	0.06	0.10
Bank and Year FE	Yes	No	Yes	No	Yes	No
Bank × Year FE	No	Yes	No	Yes	No	Yes

Table A3: Bankers' switching and size of client portfolio: Number Deals
This table shows regressions of an indicator value (in %) for the first year a banker appears at a new bank on the number of deals that the banker signs with her client portfolio at the bank. Columns (3) and (4) show the portfolio characteristics by clients' size. Columns (5) and (6) explore the trade off between the quantity and quality of the client portfolio by treating the single contact and multiple contact clients separately. The sample covers all banker-years pairs between 1996 and 2013. Variables are defined as in Appendix Table A1. t-statistics, based on robust standard errors clustered two dimensionally at lender and bank level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Dep. variable:	Banker hired (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Total #Deals$_{t-1}$	0.14***	0.10***				
	(4.66)	(4.05)				
#Deals - Small$_{t-1}$			0.38**	0.18		
			(2.02)	(1.10)		
#Deals - Large$_{t-1}$			0.16***	0.11***		
			(3.99)	(3.35)		
#Deals - Single contact$_{t-1}$					0.08**	0.11***
					(2.19)	(2.79)
#Deals - Mult. contact$_{t-1}$					0.06	-0.02
					(1.29)	(-0.52)
Observations	46,075	39,992	46,075	39,992	46,075	39,992
R-squared	0.11	0.21	0.11	0.21	0.11	0.21
Bank and Year FE	Yes	No	Yes	No	Yes	No
Bank × Year FE	No	Yes	No	Yes	No	Yes

Table A4: Initiation - Only new clients
This table shows regressions of an indicator for a new bank-borrower relationships on a dummy for personal relationship acquired. The dummy identifies clients with whom bankers that switch banks have personal relationships from past employments. The dependent variable is an indicator for new bank-borrower relationships. The sample is at the bank-borrower-year level and spans from 1996 to 2013. Bond ans SEO underwriting as well as M&A advisory deals are retrieved from CapitalIQ. Syndicated loans are from Dealscan. Variables are defined as in Appendix Table A1. t-statistics, based on robust standard errors clustered two dimensionally at firm and lender level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Dep. variable:	Initiation_strict					
	(1)	(2)	(3)	(4)	(5)	(6)
Rel_acq	0.06**	0.07**	0.11***	0.12***		
	(2.42)	(2.51)	(3.92)	(4.11)		
Rel_acq^{5yr}					0.11***	
					(3.86)	
Rel_acq^{abs}						0.06***
						(3.31)
Observations	861,444	861,444	861,444	861,444	847,102	834,461
R-squared	0.03	0.07	0.08	0.40	0.39	0.39
Year FE	Yes	Yes	Yes	No	No	No
Firm FE	Yes	No	No	No	No	No
Bank FE	Yes	No	No	No	No	No
Firm-Bank FE	No	Yes	Yes	Yes	Yes	Yes
Bank-Year FE	No	No	Yes	Yes	Yes	Yes
Firm-Year FE	No	No	No	Yes	Yes	Yes

Table A5: Deal Volume - Industry and HQ FEs

This table shows regressions of XXX Variables are defined as in Appendix Table A1. t-statistics, based on robust standard errors clustered at firm and lender level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Dep. variable:	Log Deal Volume					
	(1)	(2)	(3)	(4)	(5)	(6)
Rel_acq	0.49***			0.52***		
	(4.56)			(4.11)		
Rel_acq^{5yr}		0.52***			0.51***	
		(4.41)			(3.61)	
Rel_acq^{abs}			3.12***			3.11***
			(5.50)			(5.11)
Observations	907,578	906,154	904,621	421,086	420,074	418,702
R-squared	0.22	0.22	0.22	0.26	0.26	0.26
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Industry-Year FE	Yes	Yes	Yes	No	No	No
Bank-HQ-Year FE	No	No	No	Yes	Yes	Yes

Table A6: Initiation and Deal Volume - Pre vs. post

This table shows regressions of XXX Variables are defined as in Appendix Table A1. t-statistics, based on robust standard errors clustered at the firm level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Dep. variable:	Initiation			Log Deal Volume		
	(1)	(2)	(3)	(4)	(5)	(6)
Rel_acq	0.04***	0.05***	0.06***	2.64***	2.61***	2.62***
	(4.11)	(5.60)	(6.49)	(12.40)	(12.23)	(12.26)
Observations	56,505	50,417	50,406	52,172	45,947	45,936
R-squared	0.13	0.50	0.58	0.00	0.49	0.57
#Years	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	No	Yes	Yes
Bank FE	No	No	Yes	No	No	Yes

Table A7: Initiation - Ignoring first bank-borrower-year

This table shows regressions of an indicator for a new bank-borrower relationships on a dummy for personal relationship acquired, which identifies deals with the old clients of bankers that switch employers. The first bank-borrower-year is dropped for all acquired personal relationships. The dependent variable in Panel A includes new bank-borrower relationship as well as clients with whom the bank had no interaction in the past 5 years. The dependent variable in Panel B includes only first-time clients. The sample is at the bank-borrower-year level and spans from 1996 to 2013. Bond ans SEO underwriting as well as M&A advisory deals are retrieved from CapitalIQ. Syndicated loans are from Dealscan. Variables are defined as in Appendix Table A1. t-statistics, based on robust standard errors clustered at firm and lender level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Panel A: Initiation

Dep. variable:	Initiation					
	(1)	(2)	(3)	(4)	(5)	(6)
Rel_acq_nofirst	0.07**	0.09**	0.14***	0.15***		
	(2.35)	(2.35)	(3.61)	(3.87)		
Rel_acq_nofirst^{5yr}					0.14***	
					(3.59)	
Rel_acq_nofirst^{abs}						0.09***
						(3.61)
Observations	858,851	858,851	858,851	858,851	844,504	834,661
R-squared	0.03	0.08	0.09	0.42	0.41	0.41
Year FE	Yes	Yes	Yes	No	No	No
Firm FE	Yes	No	No	No	No	No
Firm-Bank FE	No	Yes	Yes	Yes	Yes	Yes
Bank-Year FE	No	No	Yes	Yes	Yes	Yes
Firm-Year FE	No	No	No	Yes	Yes	Yes

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Panel B: Initiation - New clients only

Dep. variable:	Initiation_strict					
	(1)	(2)	(3)	(4)	(5)	(6)
Rel_acq_nofirst	0.06**	0.08**	0.12***	0.12***		
	(2.40)	(2.47)	(3.96)	(4.22)		
Rel_acq_nofirst^{5yr}					0.12***	
					(3.94)	
Rel_acq_nofirst^{abs}						0.08***
						(3.75)
Observations	858,851	858,851	858,851	858,851	844,504	834,661
R-squared	0.03	0.07	0.08	0.40	0.39	0.39
Year FE	Yes	Yes	Yes	No	No	No
Firm FE	Yes	No	No	No	No	No
Firm-Bank FE	No	Yes	Yes	Yes	Yes	Yes
Bank-Year FE	No	No	Yes	Yes	Yes	Yes
Firm-Year FE	No	No	No	Yes	Yes	Yes

Table A8: Total deal volume - Ignoring first bank-borrower-year

This table shows regressions of the logarithm of total deal volume on an indicator for personal relationship acquired, which identifies deals with the old clients of bankers that switch employers. The indicator variable takes the value of one for all years after the banker switches. The first bank-borrower-year is dropped for all acquired personal relationships. Firms for which a relationship is acquired but never close a deal with the bank are dropped. The sample is at the bank-borrower-year level and spans from 1996 to 2013. Bond and SEO underwriting as well as M&A advisory deals are retrieved from CapitalIQ. Syndicated loans are from Dealscan. Variables are defined as in Appendix Table A1. t-statistics, based on robust standard errors clustered at firm and lender level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Dep. variable:	Log Deal Volume					
	(1)	(2)	(3)	(4)	(5)	(6)
Rel_acq_nofirst	0.56***	0.59***	0.50***	0.26***		
	(6.02)	(3.23)	(3.82)	(2.84)		
Rel_acq_nofirst^{5yr}					0.24**	
					(2.46)	
Rel_acq_nofirst^{abs}						0.42***
						(3.66)
Observations	809,081	809,081	809,081	809,081	807,628	806,429
R-squared	0.07	0.14	0.16	0.51	0.51	0.51
Year FE	Yes	Yes	Yes	No	No	No
Firm FE	Yes	No	No	No	No	No
Firm-Bank FE	No	Yes	Yes	Yes	Yes	Yes
Bank-Year FE	No	No	Yes	Yes	Yes	Yes
Firm-Year FE	No	No	No	Yes	Yes	Yes

Table A9: Total deal volume - Interaction with initiation, new clients only
This table shows regressions of the logarithm of total deal volume on an indicator for personal relationship acquired, which identifies deals with the old clients of bankers that switch employers. The indicator variable takes the value of one for all years after the banker switches. This variable is interacted with an indicator for new bank-borrower relationships, *Init. Strict*. Firms for which a relationship is acquired but never close a deal with the bank are dropped. The sample is at the bank-borrower-year level and spans from 1996 to 2013. Bond and SEO underwriting as well as M&A advisory deals are retrieved from CapitalIQ. Syndicated loans are from Dealscan. Variables are defined as in Appendix Table A1. t-statistics, based on robust standard errors clustered at firm and lender level, are reported in parentheses. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Dep. variable:	Log Deal Volume					
	(1)	(2)	(3)	(4)	(5)	(6)
Rel_acq × Init. Strict	2.08***	1.92***	1.88***	1.14***		
	(7.34)	(4.21)	(4.75)	(3.73)		
Rel_acq	0.53***	0.57***	0.50***	0.28***		
	(5.52)	(3.09)	(3.59)	(3.16)		
Init. Strict	4.83***	4.55***	4.52***	3.41***		
	(78.36)	(66.65)	(72.76)	(32.67)		
Rel_acq^{5yr} × Init. Strict					1.03***	
					(2.73)	
Rel_acq^{5yr}					0.34***	
					(3.65)	
Init. Strict					3.42***	
					(32.96)	
Rel_acq^{abs} × Init. Strict						2.31***
						(8.29)
Rel_acq^{abs}						2.43***
						(6.08)
Init. Strict						3.42***
						(33.29)
Observations	921,504	921,504	921,504	809,173	807,720	806,190
R-squared	0.11	0.18	0.19	0.52	0.52	0.52
Year FE	Yes	Yes	Yes	No	No	No
Firm FE	Yes	No	No	No	No	No
Firm-Bank FE	No	Yes	Yes	Yes	Yes	Yes
Bank-Year FE	No	No	Yes	Yes	Yes	Yes
Firm-Year FE	No	No	No	Yes	Yes	Yes