Human Capital and Local Credit Supply: Evidence from the Mortgage Industry [†]

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Abstract

This paper investigates the interaction between the labor market for loan officers and local residential mortgage markets. We find that shocks to local mortgage demand have little effect on the number of local loan officers but affect their average workloads and the fraction of remotely originated mortgages. However, evidence from shocks to the supply of local loan officers shows that these responses are not perfect substitutes for the presence of loan officers. Local loan officers increase access to mortgage credit, the efficiency of the mortgage application process, and households' refinancing decisions. Overall, our findings suggest that labor immobility can distort local credit supply and reduce capital allocation efficiency.

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1. Introduction

Over the past half century, technological innovations and financial deregulation have facilitated the integration of credit markets. Although these developments increased the flow of financial capital across regions, financial intermediation remains largely a local business (Petersen and Rajan, 2002; Becker, 2007; Gilje, Loutskina, and Strahan, 2016; Nguyen, 2019). For example, as we show in Figure 1, the median distance between mortgage lenders and the homes they finance during our sample period 2014-2022 is around 20 miles, which is not much different than the distances reported in the 2004 Survey of Consumer Finances.[1] A plausible explanation for the importance of local lending is the services and advice provided by local loan officers.

[Insert Figure 1 Here]

This paper investigates the interaction between the labor market for loan officers and local credit markets, focusing specifically on the U.S. residential mortgage market. We do this by combining a nationwide registry of over 350,000 loan officers with a comprehensive record of more than 60 million mortgage originations from 2014 to 2022. This data allows us to measure the number of individual loan officers by firm and location and to track their movements over time, providing a unique window for studying how local loan officers respond to and influence local credit markets.

Our first set of tests examines how the labor market for loan officers responds to county-level mortgage demand shocks. We measure exogenous shocks to local demand both for home purchase loans—based on the number of applications (Fuster et al., 2019)—and for refinance loans, using the number of mortgages predicted to be refinanced in each county, based on the existing mortgage stock and prevailing interest rates. The labor market potentially responds to these demand shocks in several ways. First, the number of loan officers in affected counties

[1] In Figure IA.1, we plot the time trend of mean and median lending distances from 2014 to 2022.

may adjust. We find, however, a statistically and economically insignificant relationship between the number of loan officers in counties and mortgage demand shocks. Second, the existing loan officers may adjust their workloads. Indeed, we find that local officers tend to originate more mortgages on average when local demand increases. Third, in counties with positive demand shocks, borrowers may obtain mortgages remotely. We find that the share of remotely originated loans increases, suggesting that remote lending does substitute for local mortgage supply.

If adjustments in local loan officer workloads and remote lending activities fully absorb mortgage demand shocks, the number of loan officers in a county would be irrelevant for local mortgage markets. Our second set of tests, however, shows that exogenous shocks to a county's supply of loan officers do impact the volume of mortgages originated for properties located in that county. To identify this effect, we use as an instrument the weighted average growth rate of lenders' loan officers outside the county, where the weight is the number of each lender's existing loan officers in that county. The identifying assumption is that changes in lenders' loan officer workforce in other regions are orthogonal to unobserved, county-specific shocks affecting local mortgage activity.

Using this instrument, we show that an interquartile increase in the growth of local loan officers (from -11.5% to 10.0%) causes approximately a 14.0% increase in the number of loan originations. This finding indicates that increased loan officer workloads and remote lending do not fully substitute for the supply of local loan officers. Hence, the geographical distribution of lenders' human capital does matter for credit supply.

To gain further insights, we separately examine home purchase loans and refinance loans and find that the growth of local loan officers has a larger impact on refinance loans. This finding reflects the differing demand characteristics of these two markets: demand for home purchase loans is tied to housing transactions, which are less influenced by the availability of local loan officers. In contrast, demand for refinance loans is discretionary and may be

influenced by loan officers who actively reach out to potential clients.

We next examine how the services of local loan officers provide value to borrowers, finding that they significantly improve the efficiency of both the mortgage application and refinancing processes. First, a greater supply of local loan officers reduces application withdrawals, suggesting that their advice helps borrowers navigate the process more successfully. Second, we find that the presence of local loan officers increases the percentage of "in-the-money" refinancing opportunities that are ultimately refinanced.[2] We find a negative, yet statistically insignificant, effect on loans where refinancing is not profitable, which supports the hypothesis that loan officers act as valuable facilitators of these transactions.

Given that local loan officers matter for credit supply, the finding that the number of loan officers is unresponsive to mortgage demand shocks is surprising. Our final set of tests seeks to understand this fact by exploring the frictions in the market for loan officers. We find that seasoned loan officers hired from a different county originate significantly fewer loans than their local counterparts within the same branch. This productivity gap persists for multiple years after hiring, but does not exist among loan officers who relocate internally within the firm. We also find that lending distance significantly increases after loan officers move to a different county. Overall, these findings suggest that, in addition to the costs of moving, the slow build-up of local professional networks and asymmetric information about worker productivity could impede loan officers from moving to locations with increasing mortgage demand.

Our paper makes several important contributions to the literature. We first add to studies on how access to nearby financial institutions affects economic outcomes, ranging from financial inclusion (e.g. Célerier and Matray, 2019; Sakong and Zentefis, 2024), to small business lending (e.g. Nguyen, 2019), to economic growth (e.g. Jayaratne and Strahan, 1996). While studies show that proximity improves mortgage lending outcomes (e.g. Mayer, 2024),

[2]We classify existing mortgages as "in-the-money" refinancing opportunities if the national rate has fallen at least 100 basis points since the time of origination.

and that the mortgage market is transitioning away from traditional banks toward shadow banks (e.g. Buchak et al., 2018), we use novel loan officer-mortgage linked data to show that even during this transition, much of the mortgage market remains local, and lenders' human capital in local markets is an important factor for credit supply.

Our paper also contributes to the literature on human capital in the financial industry. While studies have examined industry trends (e.g. Philippon and Reshef, 2012), patterns across financial firms (e.g. Egan, Matvos, and Seru, 2019), and the importance of individual workers' human capital,[3] few studies have examined how the spatial distribution of human capital affects the provision of financial services. Gao, Wu, and Zhang (2024) show that bank branch managers' past experiences affect mortgage lending patterns at their branch, consistent with local human capital mattering. Huang et al. (2024) show that within cities, lenders tend to allocate their less-skilled workers to lower income neighborhoods. We contribute to this literature by documenting how frictions in finance labor markets impede the flow of human capital across geographic areas, and ultimately affect the supply of financial services.

Our findings also add to the nascent literature on capacity constraints in mortgage lending. The literature has focused on how lender and loan officer constraints affect lending (e.g. Sharpe and Sherlund, 2016; Fuster et al., 2019, 2021; Choi, Choi, and Kim, 2022; Ma, 2023; Fuster, Lo, and Willen, 2024; Frazier and Goodstein, 2025). Using novel microdata where we can observe individual workers' productivity across firms and over time, we provide the first direct evidence on how labor market frictions and the supply of local loan officers affect the supply of mortgage credit.

[3]See, for example, studies on corporate loan officers (e.g. Engelberg, Gao, and Parsons, 2012; Liberti, 2018; Bushman et al., 2021; Herpfer, 2021; Carvalho, Gao, and Ma, 2023), real estate agents (e.g. Barwick et al., 2025), stock market analysts (e.g. Barber et al., 2001; Crane and Crotty, 2020), and financial analysts (e.g. Hwang, Liberti, and Sturgess, 2019).

2. Data

We combine data from several sources. First, we build the first nationwide panel of mortgage loan officers based on licensing and registration information from NMLS Consumer Access^{SM} from 2012 to 2022 (see also Huang et al., 2024). Second, we merge loan officers to data from CoreLogic on residential mortgages in order to identify the loans they originate. Finally, we obtain data on mortgage rates and refinance information from the Home Mortgage Disclosure Act, Fannie Mae, and Freddie Mac. We supplement these datasets with information on county-level demographic and economic characteristics from the U.S. Census Bureau, the Bureau of Labor Statistics (BLS), the Bureau of Economic Analysis (BEA), and the Federal Deposit Insurance Corporation (FDIC) Summary of Deposits. Appendix A provides detailed variable definitions.

2.1. NMLS loan officer data

The Secure and Fair Enforcement for Mortgage Licensing Act (SAFE Act) was passed in 2008 to protect consumers and combat fraud in the mortgage market. The law requires all residential mortgage loan officers to be in the Nationwide Mortgage Licensing System. Loan officers working for federally insured depository institutions, credit unions, and their subsidiaries must be federally registered, while other loan officers, such as those working at mortgage companies, must be state-licensed. By 2012, all state and federal regulators had integrated such regimes with the NMLS, making it a comprehensive registry of mortgage lenders and their loan officers.

We obtain access to data from NMLS Consumer Access^{SM} through an agreement with the State Regulatory Registry, a subsidiary of the Conference of State Bank Supervisors (CSBS) tasked with operating the NMLS.[4] Specifically, we obtain historical snapshots taken at the end of each calendar year from 2012 to 2022 on licenses, registrations, and other information

[4]For information on NMLS Consumer Access^{SM}, see https://nmlsconsumeraccess.org/.

for individual loan officers. At the initial registration, each loan officer is assigned a unique NMLS ID, which stays with the same loan officer over time and across employment spells, allowing us to accurately track them throughout their career in the mortgage industry.[5] By tracking loan officers over time, we construct a national panel of mortgage loan officers that contains their name, NMLS ID, employment history, and physical job location. The NMLS data also include the office addresses of loan officers, which makes it possible to identify the exact branch at which each loan originated.

We control for loan officer demographic characteristics such as race and gender while studying lending behavior. However, we do not directly observe the race and gender of loan officers in the NMLS data. Following Ambrose, Conklin, and Lopez (2021) and Frame et al. (2025), we infer loan officer race using the Bayesian Improved First Name Surname Geocoding (BIFSG) method, which is based on each individual's first name, last name, and location. Throughout our analyses, we control for Minority, an indicator for the person being non-white. To identify loan officer gender, we follow Huang, Mayer, and Miller (2024) by matching loan officer first names to the most popular first names by gender between 1950 and 2010 published by the Social Security Administration. For names that we could not identify gender clearly, we carry out an extensive search using LinkedIn profiles, company websites, and other material available on the Internet.

2.2. Mortgage transaction data

We obtain mortgage transaction data from CoreLogic, a leading provider of data on real estate and mortgage transactions. The database covers nearly all residential mortgages in the United States starting in the early 2000s. We extract property information (such as location) and mortgage characteristics (such as mortgage amount and origination date). Most importantly, for each transaction, the dataset provides the NMLS ID starting in 2014, which

[5] If a loan officer leaves the mortgage industry then rejoins at a later year, the NMLS ID remains the same.

allows us to identify the loan officer who originates the loan.

We define an individual as a mortgage loan officer if the person's NMLS ID has mortgage origination(s) in CoreLogic in a given year. For our loan officer-level analysis, we aggregate each loan officer's mortgage transactions to the yearly level to match the frequency of our NMLS panel. Specifically, we calculate the number and total dollar volume of loan originations for each loan officer-year. We then merge the CoreLogic information with our NMLS loan officer panel by NMLS ID and year. The merged data set includes each loan officer's employment history and sales performance from 2014 to 2022.

2.3. County-year panel

The majority of our analysis utilizes a county-year level dataset. We construct this dataset by combining the mortgage transaction data from CoreLogic and our loan officer-year panel. First, we aggregate the CoreLogic data to the county-year level to measure the total number of loans and dollar volume of loan originations, based on the property location. We also compute the same statistics for home purchase and refinance loans separately. Second, we take the loan officer-year panel and count the number of loan officers in each county and year, based on the registered office addresses. Third, we merge these two county-year level datasets based on county FIPS code and year. Our county-year panel spans the years 2014 to 2022.

We add information from several additional sources to this county-year panel. First, we use data from the U.S. Census Bureau, BLS, and BEA to measure local economic conditions and demographics. We group per capita income, unemployment rate, and house price growth into *local economic controls*. We also include *demographics controls*, i.e., population density, the share of the population with a college degree, and the share of the population that is white, to control for demographic information at the county-year level. Second, we augment our data with information on local bank branches from the FDIC Summary of Deposits. We calculate the number of branches, total deposits, fraction of small banks, and HHI based on

the number of branches to control for the availability of financial institutions. We collectively call these variables *local bank controls*. To mitigate the impact of outliers on regression estimates, we winsorize all variables defined as percentage changes in the county-year panel at the 1% and 99% levels.

2.4. HMDA and GSE data

We use the public version of the Home Mortgage Disclosure Act (HMDA) database for data on home purchase mortgage applications. Since 2018, the HMDA data also provide loan-level mortgage rates at origination, along with granular information on loan characteristics, borrower characteristics, as well as the county of the financed property. We use the HMDA data for three main purposes: (1) to construct our measure for home purchase loan demand, (2) to calculate residualized mortgage interest rates, and (3) to calculate the application withdrawal rates.

We also obtain from Fannie Mae and Freddie Mac (the "GSEs"), monthly loan performance datasets for single-family mortgages that serve as collateral for agency mortgage backed securities. These datasets track individual loans and provide information on their remaining balance, repayment, and delinquency conditions. We use the GSE data to construct our refinance demand measure and to calculate the fraction of loans refinanced.

2.5. Summary statistics

We present summary statistics in Table 1. Panel A reports statistics for variables in our county-year panel between 2015 and 2022.[6] The average loan officer growth rate in a county is around 1.2%. For the average county-year, the loan growth rate is around 16% and 25%, measured by the change in the number of loans and the dollar volume, respectively.

[6]The analysis panel starts in 2015 rather than 2014 to allow for the computation of year-over-year change variables.

Panel B reports variables in our loan officer-year panel between 2015 and 2022. We define all the variables in Appendix A. Our samples include over 350,000 mortgage loan officers working at 25,000 lending institutions. Roughly 57% of loan officers are male and 11% are racial/ethnic minorities. The average loan officer originates 32 loans per year, totaling slightly under $9 million, and has been working in the mortgage industry for just under 3 years. Another notable feature of the statistics is that the labor market for seasoned loan officers is particularly local. Around 60% and 57% of the external and internal seasoned hires, respectively, happen within the same county.

[Insert Table 1 Here]

3. Response to local mortgage demand shocks

In this section, we first examine how loan officer supply responds to local mortgage demand shocks. Next, we explore additional ways in which lenders may respond to shocks to mortgage demand, including workload per officer, remote lending, and mortgage pricing.

3.1. Local supply of loan officers

We begin our analysis by examining how the supply of loan officers responds to local mortgage demand shocks. To do so, we construct proxies for shocks to the demand for home purchase and refinance loans in a county. For home purchase loans, we construct a proxy for demand shocks in the spirit of Fuster et al. (2019), by calculating the annual percentage change in the number of home purchase mortgage applications in the county based on HMDA data. These mortgage application volumes in the United States vary substantially across locations and over time, which is primarily driven by local factors affecting home purchase activity.

For refinance loans, we use the fact that borrowers tend to refinance when the prevailing mortgage interest rate decreases. Unlike home purchase loans, in which loan applications are

driven by housing transactions, applications for refinance loans could be more directly affected by the availability of loan officers. Therefore, we construct a proxy for refinance demand as the annual percentage change in the number of loans in a county that are predicted to be refinanced due to national mortgage interest rate changes. More specifically, we track mortgages that are active at the end of each year in the GSE data and calculate an interest rate differential between the current maturity-matched national mortgage rate (from FRED) and the mortgage's original interest rate. For each year, we sort all mortgages into 22 bins based on the interest rate differential in 20-basis-point increments from -2% to +2% (with one bin each for <-2% and >2%). Using the fraction of loans within each bin that are refinanced at the national level as the probability of refinancing, we calculate the number of existing loans in a county that are predicted to be refinanced.[7]

We first carry out tests to confirm that our proxies indeed capture fluctuations in mortgage demand. In Table 2 Panel A column (1), we regress annual percentage change in the number of home purchase loans originated in a county on our proxy for demand shocks for home purchase loans, along with county and year fixed effects. We find that our proxy correlates strongly and positively with home purchase loan originations. In column (2), we saturate the model with *local bank controls*, *local economic controls*, and *demographics controls* to account for the availability of capital, local economic conditions, and demographics at the county level, respectively, and find similar results. In columns (3) and (4), we follow the same approach but regress the annual percentage change in the number of refinance loans on our proxy for refinance demand shocks. Again, we find a strong correlation. Overall, these results indicate that our proxies effectively capture variation in local mortgage demand.

[Insert Table 2 Here]

Next, we study the response of the local loan officer workforce to mortgage demand shocks

[7]The GSE data we use for these computations contain three-digit zip codes rather than county codes. Therefore, we compute the metrics at the three-digit zip code level and then construct county metrics based on weighted averages of the overlapping three-digit zip codes.

and present the results in Table 2 Panel B. Following the same regression specification as in Panel A, we regress annual percentage changes in the number of loan officers located in a county on local mortgage demand shocks for home purchase and refinance loans in columns (1)-(2) and (3)-(4), respectively. Across all columns, our estimates for the coefficients on the demand shocks are statistically insignificant and economically small. These results suggest that the supply of local loan officers does not respond much to local mortgage demand.

Several potential concerns about our findings could arise. First, our proxies for mortgage demand shocks might not be perfectly orthogonal to mortgage supply factors. However, if this concern were valid, it would bias our estimates *toward* finding spurious correlations between changes in the loan officer workforce and mortgage demand. However, we do not find such correlations in the data. Second, lenders might improve the quality rather than the quantity of loan officers in response to demand shocks. In Table IA.1, we regress changes in loan officers' years of experience on mortgage demand shocks and find no evidence that lenders hire more experienced loan officers. Third, some licensed loan officers may originate very few loans unless mortgage demand is high. This "part time" engagement could explain why we do not observe a response in the number of loan officers. To rule out this possibility, we restrict our sample to loan officers who originate at least five loans in a year. In Table IA.2 Panel A, we find qualitatively similar results.

3.2. Lender's response

Given that shocks to the demand for mortgages have only negligible effects on changes in the number of local loan officers, we next examine lenders' alternative responses. Specifically, we consider fluctuations in the workloads of local loan officers, changes in the use of remote lending, and changes in mortgage pricing.

3.2.1. Loan officer workload

We first examine whether lenders increase the workload per officer, i.e., assign each loan officer more loans to handle, when faced with high demand for mortgages. We test this hypothesis by regressing the change in the number of loans *per officer* on the proxies for mortgage demand, along with local bank controls, local economic controls, demographics controls, county fixed effects, and year fixed effects. We present the results in Table 3. Columns (1)-(2) and (3)-(4) focus on home purchase and refinance loans, respectively.

[Insert Table 3 Here]

We find that the workload per loan officer indeed increases, both for the home purchase and refinance loans. More specifically, a 100% increase in home purchase loan demand leads to a 58% increase in loan officer workload. The effects are slightly larger for refinance loans: doubling refinance loan demand leads to a 84% increase in loan officer workload.[8] If increasing the workload of the existing loan officers fully absorbs the demand shocks, we would expect a one-to-one relationship. That is, a 1% increase in loan demand would be met by a 1% increase in the change in the number of loans handled by a given loan officer. However, the regression coefficients are less than one, suggesting that existing loan officers do not fully absorb shocks to demand.

3.2.2. Remote lending

We next examine the extent to which local loan officers can be substituted for by remote lending. Given the proliferation of Fintech and algorithmic lending processes for mortgages, remote lending has the potential to reduce the need for local human capital. Using our county-year panel, we consider the share of loans that are originated remotely as the key

[8]Again, in Table IA.2 Panel B, we restrict our sample to loan officers who originate at least five loans in a year and find qualitatively similar results.

dependent variable. We define a loan as remotely originated if the lending distance is more than 50 miles. Table 4 presents the results for home purchase and refinance loans in columns (1)-(2) and (3)-(4), respectively.

[Insert Table 4 Here]

We document a shift toward remote lending in response to increases in mortgage demand. For home purchase loans, a 100% increase in demand leads to around a 2.3 percentage points increase in the fraction of remote lending, representing a 5% increase when compared to the unconditional mean. The results are larger in magnitude for refinance loans: doubling refinance loan demand increases the fraction of remotely originated loans by more than 4.2 percentage points. Together, this evidence suggests that substitution from local to remote lending could partially mitigate the lack of response in the loan officer labor market. Our subsequent tests estimating the effects on lending activity suggest this substitution is far from complete.

3.2.3. Loan pricing

Lastly, we explore whether lenders respond to increased mortgage demand in certain areas by adjusting mortgage rates. Lenders could adjust mortgage interest rates in response to demand. To test for such effects, we compute the average residualized mortgage rate in a county-year as the dependent variable. Specifically, using transaction-level data from HMDA, we regress mortgage rate spread on bins for loan-to-value ratio-by-year and debt-to-income ratio-by-year, as well as indicators for loan type, loan purpose, borrower age, occupancy status, conforming loan status, and second lien status. We calculate the residuals and then average them at the county-year level. We then follow the approach from preceding tables to test for the effects of demand shocks and report the results in Table IA.3. Across both the home purchase and refinance loan market, we find no evidence that lenders adjust mortgage rates in response to variation in local demand.

Collectively, the documented responses should help lenders at least partially absorb fluctuations in local mortgage demand. It is possible that such adjustments could fully mitigate any shortage of local loan officers, and thus minimize the impact on local mortgage markets. In the next section, we document that this is not the case.

4. The impact of local loan officers on mortgage lending

Ultimately, we seek to estimate the causal relationship between the availability of loan officers and local mortgage market conditions. We leverage an instrumental variables approach to isolate exogenous variation in the number of local loan officers. We also provide evidence on the channel through which local loan officers affect mortgage originations by comparing home purchase and refinance loans. Lastly, we shed light on how local loan officers help improve the efficiency of mortgage applications and local borrowers' mortgage refinancing decisions.

4.1. Loan officers and mortgage originations

Simply regressing the growth rate of local loan officers on mortgage origination volume suffers from potential endogeneity concerns as loan officer growth could be correlated with other mortgage market conditions. For example, lenders' loan officer recruitment in a county and their capital supply in the county might be commonly driven by unobserved local economic shocks. We use an instrument that isolates shocks to the supply of loan officers that are plausibly exogenous to local shocks influencing mortgage market conditions.

More specifically, we instrument for a county's loan officer growth rate with the county's exposure to lenders' loan officer growth rates outside of the county under consideration. Specifically, the instrument for county c and year t, $LO\ Growth\ Exposure_{c,t}$, as defined in Equation (1), is the weighted average loan officer growth rate across lenders for their loan officers located outside of county c in year t ($\Delta LO_{j,t,-c}$), where the weights are based on the

number of lender j's loan officers in county c, year $t-1$:

$$\text{LO Growth Exposure}_{c,t} = \sum_{j} \frac{\text{LO}_{j,c,t-1}}{\text{LO}_{c,t-1}} \times \Delta\text{LO}_{j,t,-c}, \tag{1}$$

and lender j's loan officer growth rate outside of county c in year t is

$$\Delta\text{LO}_{j,t,-c} = \frac{\sum_{c' \neq c} \text{LO}_{j,t,c'}}{\sum_{c' \neq c} \text{LO}_{j,t-1,c'}} - 1 \tag{2}$$

The instrument captures a county's exposure to the lenders' firm-level loan officer growth that is unlikely to be correlated with the county's own mortgage market conditions. The exclusion restriction for our IV design is that the instrument cannot be correlated with unobserved determinants of the outcome variable. As in all IV designs, the exclusion restriction cannot be tested directly. We provide evidence, to the extent possible, consistent with this exclusion restriction in Table IA.4. Under the exclusion restriction, our IV should not correlate with proxies for our proxies for mortgage market demand shocks as well as local economic and demographic controls. Indeed, Table IA.4 shows that we find little evidence for such a correlation between our instrument and observed local variables. Overall, these covariate balance tests provide support for the exclusion restriction and our instrumental variables approach.

We present our IV results in Table 5. Columns (1) and (2) report the first stage, in which we regress the changes in the number of loan officers on our instrument, *LO Growth Exposure*, along with fixed effects and granular controls. Our first-stage regression coefficients on the instrument are positive and statistically significant at the 1% level. The estimates demonstrate that the loan officer growth rate is correlated with the instrument, with Kleibergen-Paap Wald F-statistics of over 100, suggesting a strong instrument.

[Insert Table 5 Here]

In columns (3) to (6), we carry out the analysis using the two-stage least squares approach. We focus on the changes in the number of loans (i.e., $\Delta NLoans$) as the dependent variable in columns (3)-(4). We find a positive and statistically significant relationship between loan officer growth and loan volume. Similarly, in columns (5)-(6), we focus on the changes in the total loan dollar volume (i.e., Δ *Volume*) as the dependent variable and come to the same conclusion.[9] Our results are also economically meaningful. Taking columns (4) and (6) as examples, an interquartile increase in local loan officer growth (from -11.5% to 10.0%) leads to 14.0% more loan originations and 14.4% higher increase in dollar origination volumes, respectively. Overall, our findings support the hypothesis that loan officer growth increases local loan originations.

4.2. Heterogeneous effects on home purchase and refinance loans

To gain further insights, we conduct our analysis by loan type, distinguishing between home purchase and refinance loans. We leverage the different institutional features between mortgages associated with new home purchases (*purchase*) and mortgages used to refinance (*refi*) to assess the channel through which local loan officers affect lending. These two types of mortgages vary in terms of borrower discretion, meaning the degree to which the borrower has flexibility, such as control over the timing of the loan origination. For example, in contrast to refinancing a previous mortgage, the timing of a mortgage on a new home purchase is tied to a closing date and is thus less flexible.

[Insert Table 6 Here]

We present the results across loan types in Table 6. In columns (1) and (3), we focus on home purchase loans and use $\Delta NLoans$ and $\Delta Volume$ as the dependent variables, respectively. In columns (2) and (4), we carry out the same analysis but focus on refinance loans. Our

[9]The OLS results, presented in Table IA.5, are qualitatively similar to the IV approach.

IV estimates suggest that loan officer growth mostly affects the quantity of refinance loans. The magnitude of the effect on the number of loans is 40%–70% larger for refinance loans than for home purchase loans. Overall, the results are consistent with the quantity of home purchase loans being determined primarily by house transactions, which are largely inelastic to loan officers in a county, whereas refinance loans are flexible and can be delayed. Hence, local loan officers, who actively reach out to local borrowers to refinance loans, affect loan originations primarily through the refinancing channel.

4.3. How do loan officers provide value?

We next examine how the services of local loan officers can provide value to borrowers. We first study the effects of loan officers on the efficiency of completing mortgage applications. We next examine the rol in the refinancing processes.

4.3.1. Mortgage applications

One major role of mortgage loan officers is to help borrowers navigate the mortgage application process, given the large amount of documentation required. We examine whether loan officers have an effect on mortgage application withdrawals. Using the HMDA data, we calculate the number of loans and dollar volumes that are withdrawn, and scale those by the total number of loans and dollar value, respectively. We implement the same regression specifications as in Table 5 and present the results in Table 7.

[Insert Table 7 Here]

In columns (1) and (2), the dependent variable is the change in the fraction of applications withdrawn based on the number of applications in a year. Our estimates show that the supply of loan officers significantly reduces the withdrawal rate. Columns (3) and (4) show that the results are similar when the withdrawal rate is measured by dollar volume. The effect of

local loan officers on mortgage application efficiency is also economically meaningful. Taking column (4) as an example, an interquartile increase in the growth of local loan officers (from -11.5% to 10.0%) causes approximately a 0.5% reduction in application withdrawals, which is equivalent to 24% of a standard deviation.

4.3.2. Refinancing

In turn, we explore how the supply of local loan officers affects refinancing efficiency. Using data from Fannie Mae and Freddie Mac, we consider an outstanding loan in a given year as an efficient candidate for refinance if the national rate in the year is at least 100 basis points lower than the loan's original rate (labeled as $<$ -100 bps). Similarly, we consider a loan as an inefficient candidate if the current national rate is at least 100 basis points higher than the mortgage interest rate at origination (labeled as $>$ +100 bps). For each county-year, we calculate the fraction of existing loans that are refinanced among the efficient and inefficient candidates.

In Table 8, we use our IV specification to separately estimate the effect of changes in the number of local loan officers on the fraction of existing loans that are efficiently and inefficiently refinanced during the year. In column (1), our estimates show that the supply of loan officers significantly improves the percentage of loans that are efficiently refinanced. In contrast, in column (2), the effect on the percentage of loans that are considered inefficiently refinanced is statistically insignificant. Columns (3) and (4) show that the results are similar when refinancing activity is measured based on dollar volumes rather than loan counts. The effect of local loan officers on refinancing efficiency is economically meaningful. A back-of-the-envelope calculation suggests that a 10% increase in the growth of local loan officers would lead to mortgage borrowers saving $1.86 million in interest expenses in present value terms in the average county-year.[10]

[10]We estimate loan-level NPV from refinancing existing mortgages using GSE data. In Figure IA.2, we present the distribution of the NPVs.

[Insert Table 8 Here]

In sum, these findings suggest that loan officers not only increase the quantity of mortgage originations but also aid borrowers in efficiently refinancing existing mortgages. Indeed, labor market frictions and human capital constraints could contribute to the broader lack of refinancing activity documented in the literature (e.g., Maturana and Nickerson, 2019; Agarwal et al., 2023; Agarwal, Driscoll, and Laibson, 2013).

5. Labor market frictions

So far, we have shown that local loan officers influence credit supply as well as improve borrower outcomes. However, at the same time, the supply of local loan officers does not respond to pent-up mortgage demand. Our final set of tests seeks to understand why this is the case. We explore the frictions in the labor market of loan officers. We find suggestive evidence that (1) newly relocated loan officers need time to cultivate professional networks and a client base, and (2) information asymmetry exists regarding the productivity of new hires. Those two reasons could impede the flow of human capital across regions.

Leveraging our loan officer-year panel, we observe an active labor market for seasoned mortgage loan officers, with around 170,000 job changes between 2014 and 2022.[11] However, the distance of relocation is within 20 miles for the vast majority of these job changes. The fact that most of the seasoned hires are local suggests that, in addition to moving costs, loan officers may face frictions in the labor market when they move across regions.

5.1. Client base

We document how loan officers' client base evolves after a move by comparing their post-move mortgage lending distance to that of their incumbent coworkers using our loan officer-year

[11] For 70% of the job changes, the loan officer was active in the previous year, so we could identify the previous job's branch location.

panel. We regress the distance between the loan officer's location and the property location on indicators for the loan officer being a seasoned officer who moved from the same county, or from a different county, and for the loan officer coming from the same or a different firm. All of our specifications control for loan officer characteristics, including years of experience in the mortgage business and indicators for gender and minority status. We also saturate the model with branch $\times$ year fixed effects. This stringent specification allows us to compare newly hired and incumbent loan officers within the same branch and year, thus removing any time-varying shocks at the branch level that affect loan originations.

[Insert Table 9 Here]

We present the results in Table 9. In column (1), we focus on loans originated in the first year after hiring. We find that seasoned hires, from a different county, both internal and external, originate loans with longer distances than incumbent loan officers in the years following their hiring. In columns (2) and (3), we examine lending distances in the second and third years after hiring, respectively. We continue to find that seasoned hires are more likely to originate loans from farther away. Notably, the regression coefficients decrease from year 1 to year 3, meaning the loans originated become more local over time. These findings suggest that it takes time for loan officers to re-establish a client base after job changes.[12] In columns (4) to (6), we replace the dependent variable with the median lending distance and find similar results.

In sum, the fact that it takes time for loan officers in new locations to foster professional ties and generate business could be one of the labor market frictions that explains the lack of supply of local loan officers.

[12]For example, loan officers might need to connect with local realtors to receive referrals, as documented by Barwick et al. (2025).

5.2. Loan officer productivity

Next, we examine loan officers' productivity. We follow a similar approach as in the previous subsection by comparing their post-move mortgage origination volumes to their new coworkers' productivity using the same loan officer-year panel. We present the results in Table 10. In column (1), we focus on loan officer productivity in the first year after hiring. We find that seasoned hires from a different county originate fewer loans than those from the same county. On average, seasoned hires from different counties originate 18% fewer loans than the incumbents, whereas seasoned hires from the same county originate only 6% fewer loans than the incumbents. On the contrary, internal relocation is associated with similar, if not better, ex-post performance compared to incumbents.

[Insert Table 10 Here]

In columns (2) and (3), we replace the dependent variable with future loan originations in the second and third years after hiring, respectively. We continue to find that seasoned hires originate fewer loans than the incumbents and that seasoned hires from different counties originate significantly fewer loans than seasoned hires from the same county.[13] In columns (4) to (6), we replace the dependent variable with the dollar volume of loan originations and find similar results. Taken together, the results suggest that the incumbent loan officers in a local market are more productive on average than the seasoned hires from other counties.

We conjecture that when making hiring decisions, firms have less information about a candidate's productivity than the candidate themselves, especially for those from farther away, which gives rise to a potential adverse selection problem in the labor market (e.g., Greenwald, 1986). In Table IA.6, we provide evidence consistent with this notion by studying cases where seasoned hires have prior connections to workers at the hiring branch.

[13]While the productivity gap appears to narrow at longer time horizons, our samples consist of only loan officers who originate loans in future years. This potential survivorship issue implies that our estimated productivity gap is conservative.

A seasoned loan officer's personal connections with incumbents in the new branch might help mitigate information asymmetry about the candidate's productivity. We construct two measures to capture loan officer personal connections. The first measure is based on whether the seasoned loan officer has worked with any incumbent loan officers from the new branch in the past, according to previous work history in the NMLS data. For the second measure, we use loan officers' LinkedIn user profiles and measure pre-existing personal connections based on overlapping employment and educational history between each pair of individuals. We carry out the test by using a sample of seasoned loan officers who get new jobs. We compare loan originations in the future year between hires from the same versus a different county, and between connected versus unconnected hires, both within the same branch and year.

In Table IA.6 columns (1) and (2), *Connected* is an indicator variable that equals one if the seasoned hire loan officer has overlapping work experience with incumbent loan officers from the new branch based on the NMLS data. The interaction terms between *Connected* and *Other County* are positive and statistically significant coefficients. In columns (3) and (4), we leverage the LinkedIn based connection measure. We find consistent, if not stronger, results. In sum, we find support for the notion of asymmetric information in the seasoned loan officer market; that is, personal connections could alleviate this problem.[14]

Together, our findings in this subsection suggest that local human capital cannot flexibly reallocate via the labor market due to the potential adverse selection problem, which might prevent productive loan officers from moving between institutions.

[14]In Table IA.7, we use a pairwise county-year data to examine the movement of loan officers between counties. We carry out a horse race among moving distance, social connection (Bailey et al., 2018), and lending connection. We show that loan officers' moves are positively associated with connections. These results provide further evidence that our findings are capturing the effect of information asymmetry about loan officer quality.

6. Conclusion

Although technological innovation and financial deregulation have facilitated the integration of credit markets and increased the flow of financial capital across regions, financial intermediation remains largely local. In this paper, we combine a new nationwide registry of over 350,000 loan officers with a comprehensive dataset of more than 60 million mortgages to examine how the supply of local loan officers affects lending in local mortgage markets.

Using the number of local loan officers as a key measure, we document a surprisingly weak response of lenders' human capital to local mortgage demand shocks. In addition, lenders' responses, including increasing workload per officer and shifting loan originations to remote lenders, are not sufficient to fully mitigate any shortage of local loan officers and thus minimize the impact on local mortgage markets.

Leveraging an instrument that isolates shocks to the supply of loan officers and at the same time remains orthogonal to unobserved local factors influencing mortgage demand, we find strong evidence that lenders' local human capital has a significant effect on the number of mortgages originated in a county. We also document that local loan officers can provide value to borrowers: they significantly improve the efficiency of both the mortgage application and refinancing processes.

Our paper also shows that the slow build-up of local professional networks and asymmetric information about worker productivity could impede loan officers from moving to locations with increasing mortgage demand. Overall, our findings suggest that labor market frictions and human capital likely play an important role in local credit supply.

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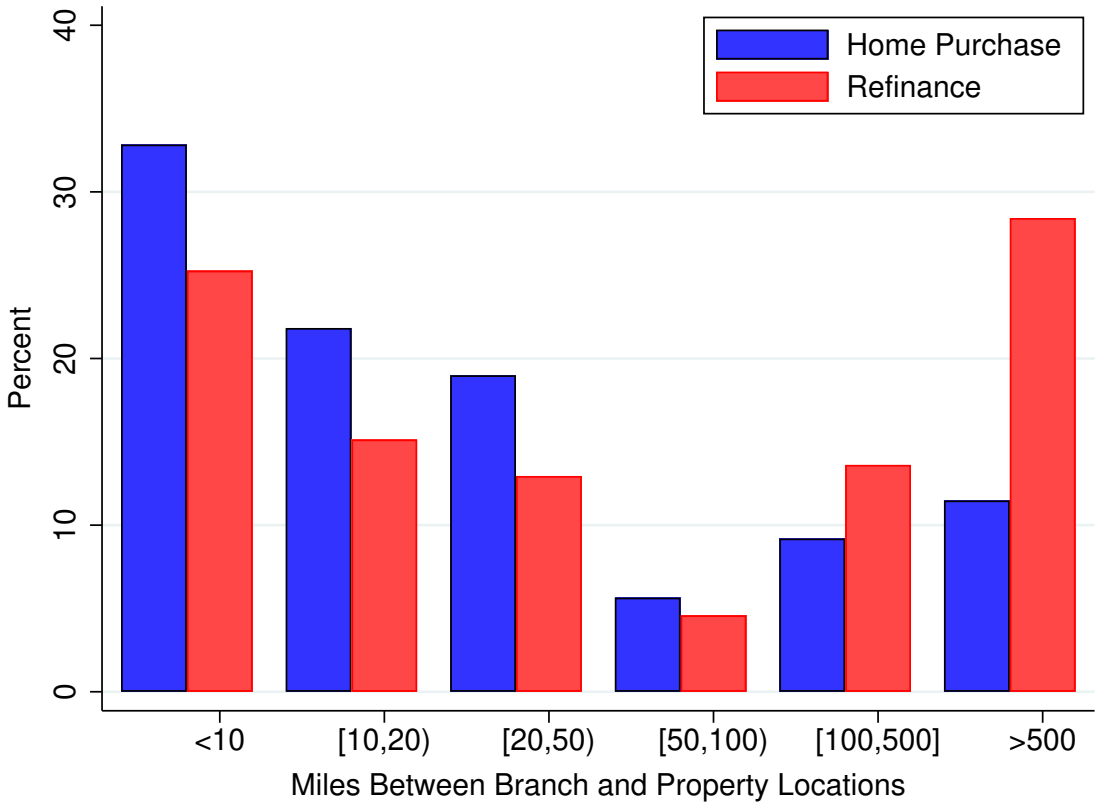


Figure 1: **Lending Distance in the US Residential Mortgage Market: 2014–2022**
This figure presents the lending distance of 62 million US mortgage loans originated between 2014 and 2022 by loan purpose. Lending distance is measured as the straight line distance (in miles) between the property location and the originating loan officer's branch location, both at the zip code level.

Table 1: **Summary Statistics**

This table presents summary statistics for the variables used in the analyses. Panel A summarizes variables in the county-year panel sample between 2015 and 2022. Panel B summarizes variables in the loan officer-year panel sample. We present the sample size (N), mean, standard deviation (SD), 25th percentile (P25), 50th percentile (P50), and 75th percentile (P75) in columns (1)–(6), respectively. Appendix A defines all variables.

Panel A: County-Year Sample

	N	Mean	SD	P25	P50	P75
	(1)	(2)	(3)	(4)	(5)	(6)
ΔLO	14,292	1.2%	23.5%	-11.5%	0.0%	10.0%
ΔDemand: Purchase	14,292	5.4%	15.7%	-4.2%	5.4%	14.2%
ΔDemand: Refi	14,292	19.0%	67.2%	-23.3%	2.3%	40.3%
ΔNloans	14,292	15.8%	57.1%	-9.8%	5.3%	23.2%
ΔVolume	14,292	25.3%	70.3%	-8.6%	10.6%	35.8%
ΔNloans: Purchase	14,292	17.3%	60.5%	-5.0%	5.6%	17.3%
ΔVolume: Purchase	14,292	26.0%	66.4%	0.3%	12.5%	27.1%
ΔNloans: Refi	14,292	23.7%	79.8%	-23.3%	4.0%	45.5%
ΔVolume: Refi	14,292	33.5%	94.1%	-24.3%	7.2%	65.5%
ΔNloans per LO: Purchase	14,292	20.4%	61.1%	-7.0%	6.9%	26.7%
ΔNloans per LO: Refi	14,292	25.4%	80.2%	-25.5%	4.1%	53.5%
Nloans% Remote: Purchase	14,292	48.2%	19.8%	32.3%	46.0%	62.1%
Nloans% Remote: Refi	14,292	56.6%	17.7%	43.6%	56.7%	69.4%
LO Growth Exposure	14,292	-0.8%	15.3%	-9.3%	-0.9%	6.5%
ΔNloans% Withdraw	14,292	0.7%	2.2%	-0.5%	0.6%	1.8%
ΔVolume% Withdraw	14,292	0.7%	3.5%	-0.9%	0.6%	2.3%
Nloans% Refi: Δrate <-100 bps	14,282	18.6%	8.7%	12.7%	16.0%	25.0%
Volume% Refi: Δrate <-100 bps	14,282	20.3%	10.0%	13.3%	16.9%	28.0%
Nloans% Refi: Δrate >+100 bps	11,501	6.3%	9.4%	0.0%	5.7%	8.0%
Volume% Refi: Δrate >+100 bps	11,501	6.2%	9.7%	0.0%	5.5%	7.6%

Table 1: **Summary Statistics - Continued**

Panel B: Loan Officer-Year Sample

	N	Mean	SD	P25	P50	P75
	(1)	(2)	(3)	(4)	(5)	(6)
All Loan Officer-Year:						
Nloans	1,636,525	32.3	56.1	3.0	12.0	39.0
Volume	1,636,525	8.9	27.0	0.5	2.5	9.7
Mean Lending Distance	1,636,525	245.4	522.6	16.9	36.5	126.8
Median Lending Distance	1,636,525	209.9	528.6	11.3	22.2	54.7
Experience	1,636,525	2.59	2.31	1.0	2.0	4.0
Male	1,636,525	0.57	0.50	0.0	1.0	1.0
Minority	1,636,525	0.11	0.31	0.0	0.0	0.0
External Hire Loan Officer-Year:						
Same County	119,160	0.60	0.49	0.0	1.0	1.0
Other County	119,160	0.40	0.49	0.0	0.0	1.0
Internal Move Loan Officer-Year:						
Same County	28,856	0.57	0.50	0.0	1.0	1.0
Other County	28,856	0.43	0.50	0.0	0.0	1.0

Table 2: **Response to Local Mortgage Demand Shocks**

This table explores the response of loan originations and loan officers to local mortgage demand shocks. Each observation is a county-year between 2015 and 2022. Panel A reports the results of regressing the percentage change in mortgage originations in a county on proxies of mortgage demand shocks in the county. Panel B replaces the dependent variable with the percentage change in the number of loan officers in a county. Columns (1)-(2) and (3)-(4) focus on home purchase loans and refinance loans, respectively. Demand shocks for home purchase loans and refinance loans are measured with the growth of home purchase loan applications and the growth of refinance loans induced by mortgage rate changes, respectively. *Local bank controls* include changes in branches per capita, deposits per capita, average bank size, and HHI based on number of branches. *Local economic controls* include the change in per capita income, unemployment rate, and house price growth. *Demographics controls* include changes in shares of households with a college degree, minority population share, and population density. Standard errors, clustered at the county level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Panel A: Change in Number of Loan Originations

	Purchase		Refi	
	(1)	(2)	(3)	(4)
ΔDemand: Purchase	0.586***	0.575***		
	(0.034)	(0.034)		
ΔDemand: Refi			0.949***	0.959***
			(0.154)	(0.154)
Local Bank Controls	N	Y	N	Y
Local Economic Controls	N	Y	N	Y
Demographics Controls	N	Y	N	Y
County FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
N	14,252	14,252	14,252	14,252
R^2	0.427	0.428	0.644	0.645

Panel B: Change in Number of Loan Officers

	(1)	(2)	(3)	(4)
ΔDemand: Purchase	0.034	0.031		
	(0.021)	(0.021)		
ΔDemand: Refi			0.024	0.037
			(0.060)	(0.060)
Local Bank Controls	N	Y	N	Y
Local Economic Controls	N	Y	N	Y
Demographics Controls	N	Y	N	Y
County FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
N	14,252	14,252	14,252	14,252
R^2	0.169	0.171	0.169	0.171

Table 3: **Mortgage Demand Shocks and Loan Originations Per Officer**

This table reports estimates from regressing the percentage change in the number of mortgage originations per officer in a county on proxies for mortgage demand shocks in the county. Demand shocks for home purchase loans and refinance loans are measured with the growth of home purchase loan applications and the growth of refinance loans induced by mortgage rate changes, respectively. Columns (1)-(2) and (3)-(4) focus on home purchase loans and refinance loans, respectively. *Local banks controls* include changes in branches per capita, deposits per capita, fraction of small banks, and HHI based on number of branches. *Local economic controls* include the change in per capita income, unemployment rate, and house price growth. *Demographics controls* include changes in shares of population with a college degree, white population share, and population density. Standard errors, clustered at the county level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Change in Number of Loans Per Officer

	Purchase		Refi	
	(1)	(2)	(3)	(4)
ΔDemand: Purchase	0.586***	0.581***		
	(0.045)	(0.045)		
ΔDemand: Refi			0.836***	0.837***
			(0.178)	(0.177)
Local Bank Controls	N	Y	N	Y
Local Economic Controls	N	Y	N	Y
Demographics Controls	N	Y	N	Y
County FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
N	14,252	14,252	14,252	14,252
R^2	0.294	0.296	0.565	0.567

Table 4: **Mortgage Demand Shocks and Reliance on Remote Lending**

This table reports estimates from regressing the share of loans in a county that are originated from more than 50 miles away on proxies for mortgage demand shocks in the county. Demand shocks for home purchase loans and refinance loans are measured with the growth of home purchase loan applications and the growth of refinance loans induced by mortgage rate changes, respectively. Columns (1)-(2) and (3)-(4) focus on home purchase loans and refinance loans, respectively. *Local banks controls* include changes in branches per capita, deposits per capita, fraction of small banks, and HHI based on number of branches. *Local economic controls* include the change in per capita income, unemployment rate, and house price growth. *Demographics controls* include changes in shares of population with a college degree, white population share, and population density. Standard errors, clustered at the county level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Share of Loans Remotely Originated

	Purchase		Refi	
	(1)	(2)	(3)	(4)
ΔDemand: Purchase	0.023***	0.025***		
	(0.005)	(0.005)		
ΔDemand: Refi			0.042***	0.043***
			(0.016)	(0.016)
Local Bank Controls	N	Y	N	Y
Local Economic Controls	N	Y	N	Y
Demographics Controls	N	Y	N	Y
County FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
N	14,252	14,252	14,252	14,252
R^2	0.925	0.926	0.903	0.903

Table 5: **Effect of Local Loan Officers on Mortgage Originations**

This table reports two-stage least squares estimates for the effect of loan officers in a county on loan originations in the county. Each observation is a county-year between 2015 and 2022. Columns (1) and (2) present the first stage estimates, in which we regress ΔLO, defined as the annual percentage change in the number of loan officers, on the instrument *LO Growth Exposure*, defined as the county's exposure to firm-level loan officer growth in other local markets. Columns (3) to (6) present the second stage estimates using the instrument. The dependent variables are the percentage change in loan originations based on the number of loans and loan dollar volume in columns (3)-(4) and (5)-(6), respectively. *Local banks controls* include changes in branches per capita, deposits per capita, fraction of small banks, and HHI based on number of branches. *Local economic controls* include the change in per capita income, unemployment rate, and house price growth. *Demographics controls* include changes in shares of population with a college degree, white population share, and population density. Kleibergen-Paap Wlad F-statistic for weak identification test is reported in the bottom row of columns (1) and (2). Standard errors, clustered at the county level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Second Stage Dependent Variable: Change in Loan Originations

	First Stage		Second Stage			
	ΔLO		ΔNLoans		ΔVolume	
	(1)	(2)	(3)	(4)	(5)	(6)
LO Growth Exposure	0.194***	0.194***				
	(0.019)	(0.019)				
ΔLO			0.565***	0.566***	0.570***	0.568***
			(0.147)	(0.148)	(0.185)	(0.185)
Local Bank Controls	N	Y	N	Y	N	Y
Local Economic Controls	N	Y	N	Y	N	Y
Demographics Controls	N	Y	N	Y	N	Y
County FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y
N	14,252	14,252	14,252	14,252	14,252	14,252
R^2	0.182	0.184				
F-statictic	106.8	105.2				

Table 6: **Effect of Local Loan Officers on Mortgage Originations By Loan Purpose**

This table reports two-stage least squares estimates for the effect of loan officers in a county on loan originations in the county by loan type. Each observation is a county-year between 2015 and 2022. The dependent variables are the percentage change in loan originations based on the number of loans and loan dollar volume in columns (1)-(2) and (3)-(4), respectively. ΔLO is annual percentage change in the number of loan officers. We instrument ΔLO with *LO Growth Exposure*, defined as the county's exposure to firm-level loan officer growth in other local markets. *Local banks controls* include changes in branches per capita, deposits per capita, fraction of small banks, and HHI based on number of branches. *Local economic controls* include the change in per capita income, unemployment rate, and house price growth. *Demographics controls* include changes in shares of population with a college degree, white population share, and population density. Kleibergen-Paap Wald F-statistic for weak identification test is reported in the last row. Standard errors, clustered at the county level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Change in Loan Originations

	ΔNLoans		ΔVolume	
	Purchase	Refi	Purchase	Refi
	(1)	(2)	(3)	(4)
ΔLO	0.345**	0.485***	0.297	0.498**
	(0.173)	(0.182)	(0.196)	(0.221)
Local Bank Controls	Y	Y	Y	Y
Local Economic Controls	Y	Y	Y	Y
Demographics Controls	Y	Y	Y	Y
County FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
N	14,252	14,252	14,252	14,252
First-stage F statistic	105.2	105.2	105.2	105.2

Table 7: **Effect of Local Loan Officers on Mortgage Application Efficiency**

This table reports two-stage least squares estimates for the effect of loan officers in a county on the efficiency of mortgage applications in the county. Each observation is a county-year between 2015 and 2022. The dependent variable is the change in the fraction of mortgage applications that are withdrawn, based on either the number of loans in columns (1) and (2) and dollar volumes in columns (3) and (4). ΔLO is annual percentage change in the number of loan officers. We instrument ΔLO with *LO Growth Exposure*, defined as the county's exposure to firm-level loan officer growth in other local markets. *Local banks controls* include changes in branches per capita, deposits per capita, fraction of small banks, and HHI based on number of branches. *Local economic controls* include the change in per capita income, unemployment rate, and house price growth. *Demographics controls* include changes in shares of population with a college degree, white population share, and population density. Kleibergen-Paap Wald F-statistic for weak identification test is reported in the last row. Standard errors, clustered at the county level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Fraction of Applications Withdrawn

	NLoans%		Volume%	
	(1)	(2)	(3)	(4)
ΔLO	-0.021**	-0.022**	-0.025**	-0.025**
	(0.009)	(0.009)	(0.012)	(0.012)
Local Bank Controls	N	Y	N	Y
Local Economic Controls	N	Y	N	Y
Demographics Controls	N	Y	N	Y
County FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
N	14,252	14,252	14,252	14,252
First-stage F statistic	106.8	105.2	106.8	105.2

Table 8: **Effect of Local Loan Officers on Refinancing Efficiency**

This table reports two-stage least squares estimates for the effect of loan officers in a county on the efficiency of refinance mortgages in the county. Each observation is a county-year between 2015 and 2022. The dependent variable is the percentage of existing mortgages that are refinanced during the year, based on the number of loans in columns (1) and (2) and dollar volumes in columns (3) and (4). In columns (1) and (3), a loan is included in the numerator when the national rate in the current year is at least 100 basis points lower than the original rate (labeled as < -100 bps). In columns (2) and (4), a loan is included in the numerator when the national rate in the current year is at least 100 basis points higher than the original rate (labeled as > +100 bps). ΔLO is annual percentage change in the number of loan officers. We instrument ΔLO with *LO Growth Exposure*, defined as the county's exposure to firm-level loan officer growth in other local markets. *Local banks controls* include changes in branches per capita, deposits per capita, fraction of small banks, and HHI based on number of branches. *Local economic controls* include the change in per capita income, unemployment rate, and house price growth. *Demographics controls* include changes in shares of population with a college degree, white population share, and population density. Kleibergen-Paap Wald F-statistic for weak identification test is reported in the last row. Standard errors, clustered at the county level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Fraction of Existing Loans Refinanced

	NLoans%		Volume%	
ΔRate of existing loans:	<-100 bps	>+100 bps	<-100 bps	>+100 bps
	(1)	(2)	(3)	(4)
ΔLO	0.025**	-0.028	0.030**	-0.019
	(0.012)	(0.034)	(0.013)	(0.035)
Local Bank Controls	Y	Y	Y	Y
Local Economic Controls	Y	Y	Y	Y
Demographics Controls	Y	Y	Y	Y
County FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
N	14,240	11,364	14,240	11,364
First-stage F statistic	106.1	87.7	106.1	87.7

Table 9: **Loan Officer Post-Relocation Lending Distance**

This table reports estimates of regressing a loan officer's lending distance on dummies indicating the loan officer's previous work location. The sample includes all loan officers in NMLS for years between 2015 and 2022. In columns (1), (2), and (3), the dependent variable is the average distance of loan originations in the next one, two, and three years, respectively. In columns (4) to (6), we replace the dependent variable with the median distance of loan originations. *External* and *Internal* are indicator variables that equal one if the loan officer is hired from another lender and if the loan officer is relocated from the another branch of the same lender, respectively. These dummies equal zero for existing loan officers in the branch. *Same County* and *Other County* indicate whether loan officer's previous work location is in the same county as the new work location. Control variables include *Experience*, *Male*, and *Minority*. Standard errors, clustered at the county level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Distance of Future Mortgage Originations

	Mean Distance			Median Distance		
	Year 1	Year 2	Year 3	Year 1	Year 2	Year 3
	(1)	(2)	(3)	(4)	(5)	(6)
External: Same County	-10.073	-4.899	-0.199	-9.399	-1.541	2.033
	(6.585)	(6.367)	(6.425)	(6.149)	(6.605)	(7.683)
External: Other County	58.940***	34.608***	31.124***	70.379***	46.070***	38.624***
	(10.786)	(7.434)	(6.741)	(11.476)	(7.302)	(6.616)
Internal: Same County	-4.255	-3.411	14.447	-4.796	3.046	22.910
	(8.458)	(7.879)	(13.876)	(8.137)	(10.104)	(15.834)
Internal: Other County	45.076***	21.745*	11.599	51.626***	26.343**	16.626
	(9.822)	(11.123)	(11.756)	(11.128)	(11.682)	(11.751)
Experience	-6.248***	-6.415***	-7.231***	-9.306***	-9.657***	-10.625***
	(1.076)	(1.297)	(1.625)	(1.168)	(1.343)	(1.668)
Male	9.938***	12.639***	13.826***	5.777***	7.962***	9.269***
	(2.214)	(2.429)	(2.459)	(2.127)	(2.313)	(2.369)
Minority	-12.378**	-17.262***	-14.300***	-6.468	-10.485*	-7.944
	(5.818)	(5.620)	(5.419)	(5.964)	(5.576)	(5.435)
Branch × Year FEs	Y	Y	Y	Y	Y	Y
N	612,395	461,946	344,881	612,395	461,946	344,881
R^2	0.745	0.697	0.663	0.696	0.649	0.615

Table 10: **Loan Officer Post-Relocation Productivity**

This table reports estimates of regressing a loan officer's loan originations on dummies indicating the loan officer's previous work location. The sample includes all loan officers in NMLS for years between 2015 and 2022. In columns (1), (2), and (3), the dependent variable is the natural logarithm of the number of loan originations in the next one, two, and three years, respectively. In columns (4) to (6), we replace the dependent variable with the natural logarithm of annual dollar origination volume. *External* and *Internal* are indicator variables that equal one if the loan officer is hired from another lender and if the loan officer is relocated from another branch of the same lender, respectively. These dummies equal zero for existing loan officers in the branch. *Same County* and *Other County* indicate whether loan officer's previous work location is in the same county as the new work location. Control variables include *Experience*, *Male*, and *Minority*. Standard errors, clustered at the county level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Quantity of Future Mortgage Originations

	Log(Nloans)			Log(Volume)		
	Year 1	Year 2	Year 3	Year 1	Year 2	Year 3
	(1)	(2)	(3)	(4)	(5)	(6)
External: Same County	-0.062***	-0.069***	-0.071***	-0.069***	-0.072***	-0.080***
	(0.012)	(0.013)	(0.014)	(0.013)	(0.013)	(0.015)
External: Other County	-0.175***	-0.142***	-0.119***	-0.185***	-0.151***	-0.135***
	(0.012)	(0.013)	(0.015)	(0.014)	(0.016)	(0.017)
Internal: Same County	0.080***	0.035*	0.024	0.089***	0.041*	0.028
	(0.017)	(0.021)	(0.031)	(0.016)	(0.022)	(0.039)
Internal: Other County	0.026	0.019	-0.013	0.030	0.031	-0.022
	(0.023)	(0.028)	(0.029)	(0.025)	(0.029)	(0.029)
Experience	0.213***	0.204***	0.207***	0.244***	0.232***	0.236***
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)
Male	0.090***	0.089***	0.083***	0.151***	0.151***	0.143***
	(0.008)	(0.009)	(0.010)	(0.009)	(0.011)	(0.012)
Minority	-0.005	-0.007	-0.005	-0.070***	-0.072***	-0.070***
	(0.013)	(0.015)	(0.016)	(0.013)	(0.016)	(0.017)
Branch × Year FEs	Y	Y	Y	Y	Y	Y
N	612,395	461,946	344,881	612,395	461,946	344,881
R^2	0.514	0.493	0.479	0.580	0.555	0.536

Appendix A. Variable Definitions

Variables	Definition
County-year sample	
ΔLO	Percentage change in the number of loan officers in a county.
ΔDemand: Purchase	Percentage change in the number of home purchase loan applications in a county.
ΔDemand: Refi	Percentage change in the number of refinance loans in the county induced by mortgage rate changes.
ΔNloans	Percentage changes in the number of mortgage loan originations in the county.
ΔVolume	Percentage changes in the dollar volume (million USD) of mortgage loan originations in the county.
ΔNloans per LO	Percentage change in the number of mortgage originations per officer in the county.
Nloans% Remote	The share of loans in a county that are originated from more than 50 miles away.
LO Growth Exposure	The county's exposure to lender-level loan officer growth in other counties.
Δrate <-100 bps	An indicator variable that equals one if the national rate in the current year is at least 100 basis points lower than the original rates for a given loan.
Δrate >+100 bps	An indicator variable that equals one if the national rate in the current year is at least 100 basis points higher than the original rates for a given loan.
Nbranches	Natural logarithm of the number of bank branches in the county
Deposits	Natural logarithm of total deposits in the county
SmallBankShare	Fraction of banks with less than $1 billion in assets
HHI(Branches)	HHI based on the number of branches in the county
Income	Per capita income at the county level
Unemployment	Unemployment rate at the county level
HouseIndex	Percentage change in Zillow housing price index in the county
Population	Total population scaled by land area size
WhiteShare	Fraction of number of white to total population
BachelorShare	The fraction of the population with a college degree
Loan officer-year sample	
Log(Nloans)	Natural logarithm of the number of loans originated in the year.
Log(Volume)	Natural logarithm of the total dollar amount of loans originated in the year.
Lending Distance	The distance (miles) between the property location and loan officer's office address.
Experience	The number of years during which the loan officer originates mortgages between 2014 and the current year.
Male	An indicator variable that equals one if the loan officer's sex is male
Minority	An indicator variable that equals one if the loan officer is non-white
Same County	An indicator variable that equals one if the loan officer's previous work location is in the same county as the new work location
Other County	An indicator variable that equals one if the loan officer's previous work location is in a different county than the new work location
Internal	An indicator variable that equals one if the loan officer is relocated from the another branch of the same lender.
External	An indicator variable that equals one if the loan officer is hired from another lender.

Human Capital and Local Credit Supply: Evidence from the Mortgage Industry

Internet Appendix

A. LinkedIn data

We obtain information on loan officers' professional and educational background from the universe of LinkedIn user profiles as of 2022, provided by the Data Bright Initiative. We match loan officers and LinkedIn user profiles in two steps. First, we construct a company-level match between lenders' company NMLS IDs and employers on LinkedIn. Second, within a company, we match loan officers and LinkedIn users based on the person's first and last names, the job location, and the beginning and ending years of the job. We are able to match 20.8% of loan officers to their LinkedIn profiles.

In our analysis, we use whether loan officers have worked at the same location according to NMLS in order to measure work connections, so that we can take full advantage of our nationwide loan officer registry. LinkedIn provides more granular information on education and work history, such as education ties and shared work experience outside of the mortgage industry. Therefore, we use the subset of loan officers matched with LinkedIn profiles to sharpen our measurement of personal connections between seasoned hire loan officers joining a branch and incumbent loan officers in the branch. From the LinkedIn profiles, we also extract additional characteristics about the loan officers, including the number of years in the mortgage industry, the total number of years in other industries, and the number of education records. We saturate our regression models with such information as additional control variables when using the LinkedIn sample.

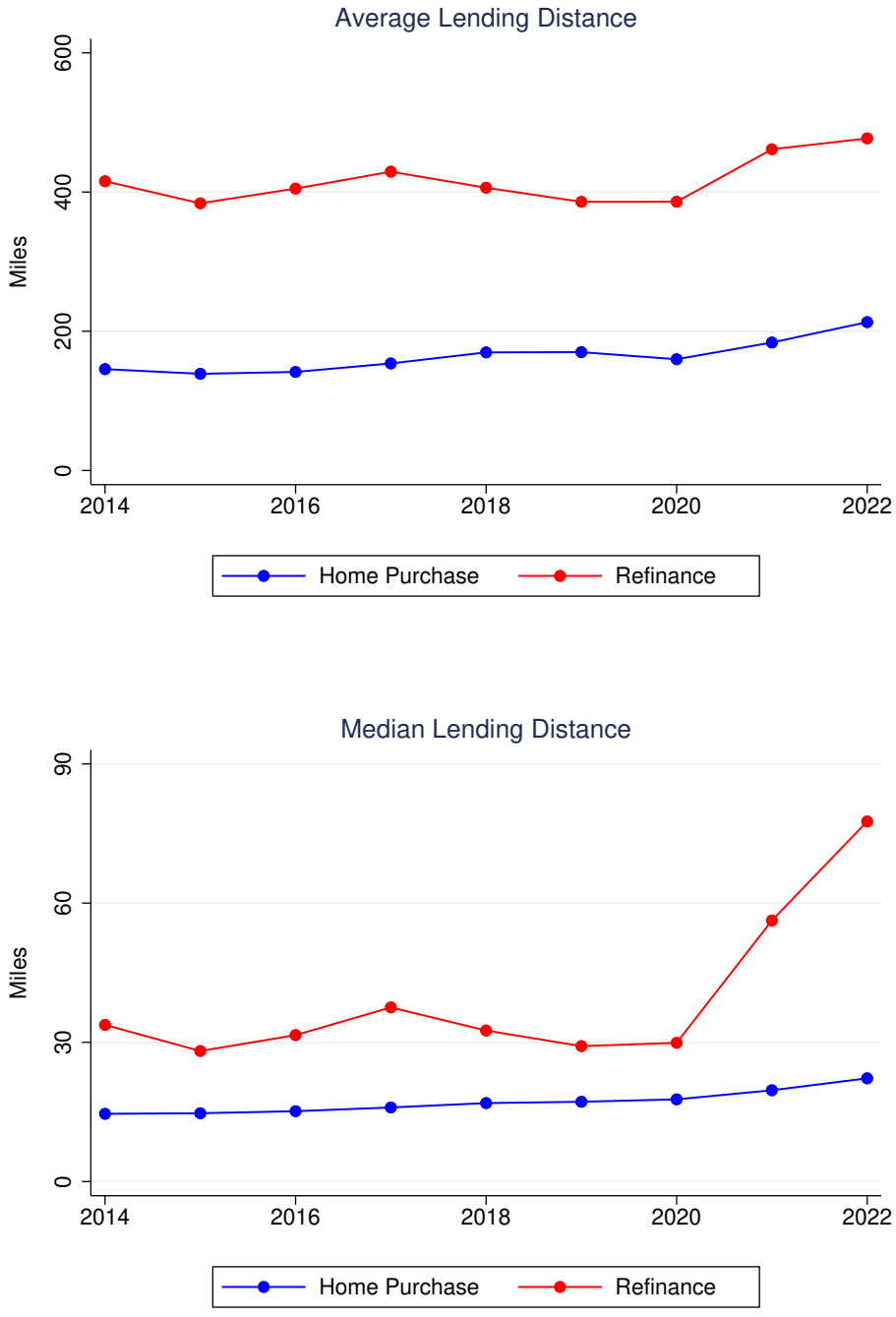


Figure IA.1: **Lending Distance: Time Trend 2014–2022.**
This figure presents annual average lending distances by loan purpose and year. Lending distance is measured as the straight line distance (in miles) between the property location and the origination loan officer's branch location, both at the zip code level.

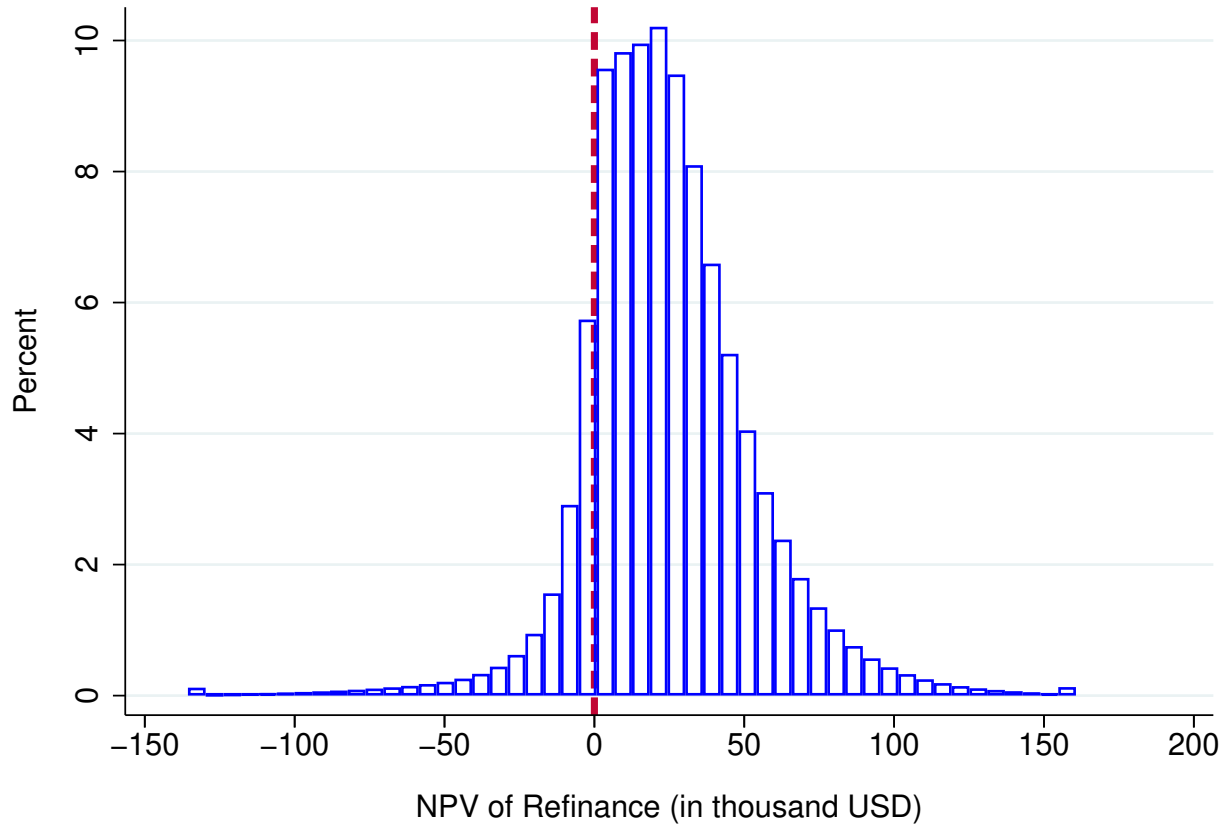


Figure IA.2: **Distribution of NPV from Refinancing Existing Mortgages**
This figure presents the distribution of NPV from refinancing existing mortgages. The sample includes all prepayment events of mortgages in Fannie Mae and Freddie Mac with at least a $70,000 remaining balance between 2012 and 2022. The NPV is estimated as the difference in the present values of monthly payment cash flows of the existing loan and a new loan that has the same remaining balance and maturity and the maturity-matched current national mortgage rate.

Table IA.1: **Mortgage Demand Shocks and Loan Officer Experience**

This table reports results of regressing the change in the average number of years in the mortgage industry among loan officers in a county on proxies of mortgage demand shocks in the county. Each observation is a county-year between 2015 and 2022. Columns (1)-(2) and (3)-(4) focus on home purchase loans and refinance loans, respectively. Demand shocks for home purchase loans and refinance loans are measured with the growth of home purchase loan applications and the growth of refinancing loans induced by mortgage rate changes, respectively. *Local banks controls* include changes in branches per capita, deposits per capita, fraction of small banks, and HHI based on number of branches. *Local economic controls* include the change in per capita income, unemployment rate, and house price growth. *Demographics controls* include changes in shares of population with a college degree, white population share, and population density. Standard errors, clustered at the county level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Change in Officer Experience

	Purchase		Refi	
	(1)	(2)	(3)	(4)
ΔDemand: Purchase	-0.016	-0.018		
	(0.049)	(0.049)		
ΔDemand: Refi			-0.321**	-0.302**
			(0.137)	(0.136)
Local Bank Controls	N	Y	N	Y
Local Economic Controls	N	Y	N	Y
Demographics Controls	N	Y	N	Y
County FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
N	14,252	14,252	14,252	14,252
R^2	0.136	0.140	0.137	0.140

Table IA.2: **Robustness: Full-Time Loan Officers**

This table reports robustness tests using loan officers who originate at least 5 loans in the year. Each observation is a county-year between 2015 and 2022. Panel A reports results of re-estimating regressions in Table 2 Panel B. Panel B reports results of re-estimating regressions in Table 3. Standard errors, clustered at the county level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Panel A: Change in Number of Loan Officers

	Purchase		Refi	
	(1)	(2)	(3)	(4)
ΔDemand: Purchase	0.021	0.020		
	(0.033)	(0.034)		
ΔDemand: Refi			0.011	0.020
			(0.105)	(0.106)
Local Bank Controls	N	Y	N	Y
Local Economic Controls	N	Y	N	Y
Demographics Controls	N	Y	N	Y
County FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
N	13,828	13,828	13,828	13,828
R^2	0.235	0.237	0.235	0.237

Panel B: Change in Number of Loans per Loan Officer

	Purchase		Refi	
	(1)	(2)	(3)	(4)
ΔDemand: Purchase	0.551***	0.546***		
	(0.044)	(0.044)		
ΔDemand: Refi			0.870***	0.878***
			(0.173)	(0.173)
Local Bank Controls	N	Y	N	Y
Local Economic Controls	N	Y	N	Y
Demographics Controls	N	Y	N	Y
County FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
N	13,649	13,649	13,649	13,649
R^2	0.211	0.212	0.519	0.520

Table IA.3: **Mortgage Demand Shocks and Loan Pricing**

This table reports results of regressing the average residualized mortgage rate in a county on proxies for mortgage demand shocks in the county. Each observation is a county-year between 2015 and 2022. Columns (1)-(2) and (3)-(4) focus on home purchase loans and refinance loans, respectively. Demand shocks for home purchase loans and refinance loans are measured with the growth of home purchase loan applications and the growth of refinance loans induced by mortgage rate changes, respectively. *Local banks controls* include changes in branches per capita, deposits per capita, fraction of small banks, and HHI based on number of branches. *Local economic controls* include the change in per capita income, unemployment rate, and house price growth. *Demographics controls* include changes in shares of population with a college degree, white population share, and population density. Standard errors, clustered at the county level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Average Residualized Mortgage Rate

	Purchase		Refi	
	(1)	(2)	(3)	(4)
ΔDemand: Purchase	-0.014	-0.014		
	(0.009)	(0.009)		
ΔDemand: Refi			0.064	0.078
			(0.053)	(0.053)
Local Bank Controls	N	Y	N	Y
Local Economic Controls	N	Y	N	Y
Demographics Controls	N	Y	N	Y
County FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
N	10,023	10,023	9,679	9,679
R^2	0.841	0.842	0.680	0.680

Table IA.4: **Balance Test for Instrumental Variable**

This table reports results of regressing the instrumental variable on proxies for mortgage demand shocks in the county. Each observation is a county-year between 2015 and 2022. *LO Growth Exposure* is the instrument, defined as average lender-level loan officer growth in other local markets, weighted by the county's exposures to lenders. Demand shocks for home purchase loans and refinance loans are measured with the growth of home purchase loan applications and the growth of refinance loans induced by mortgage rate changes, respectively. Standard errors, clustered at the county level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: LO Growth Exposure

	(1)	(2)	(3)	(4)	(5)	(6)
ΔDemand: Purchase	0.003	0.003			0.003	0.003
	(0.011)	(0.011)			(0.011)	(0.011)
ΔDemand: Refi			-0.005	0.001	-0.004	0.001
			(0.037)	(0.038)	(0.037)	(0.038)
Local bank controls						
ΔNbranches		0.011		0.011		0.011
		(0.031)		(0.031)		(0.031)
ΔDeposits		0.042*		0.042*		0.042*
		(0.025)		(0.025)		(0.025)
ΔSmallBankShare		0.021		0.021		0.021
		(0.026)		(0.026)		(0.026)
ΔHHI(Branches)		0.004		0.004		0.004
		(0.112)		(0.112)		(0.112)
Local economic controls						
ΔIncome		0.050		0.051		0.050
		(0.054)		(0.055)		(0.055)
ΔUnemployment		0.002		0.001		0.002
		(0.002)		(0.002)		(0.002)
ΔHouseIndex		0.054		0.054		0.054
		(0.038)		(0.038)		(0.038)
Demographics controls						
ΔPopulation		-0.061		-0.061		-0.061
		(0.136)		(0.136)		(0.136)
ΔWhiteShare		-0.074		-0.072		-0.074
		(0.827)		(0.827)		(0.827)
ΔBachelorShare		-0.044		-0.045		-0.044
		(0.201)		(0.201)		(0.201)
County FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y
N	14,252	14,252	14,252	14,252	14,252	14,252
R^2	0.270	0.270	0.270	0.270	0.270	0.270

Table IA.5: **Correlation Between Local Loan Officers and Mortgage Originations**

This table reports estimates from regressing changes in loan originations in a county on changes in the number of loan officers in the county. Each observation is a county-year between 2015 and 2022. The dependent variables are the percentage change in loan originations based on the number of loans and loan dollar volume in columns (1)-(2) and (3)-(4), respectively. ΔLO is the percentage change in the number of loan officers. *Local banks controls* include changes in branches per capita, deposits per capita, fraction of small banks, and HHI based on number of branches. *Local economic controls* include the change in per capita income, unemployment rate, and house price growth. *Demographics controls* include changes in shares of population with a college degree, white population share, and population density. Standard errors, clustered at the county level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Mortgage Originations

	ΔNLoans		ΔVolume	
	(1)	(2)	(3)	(4)
ΔLO	0.329***	0.328***	0.386***	0.386***
	(0.026)	(0.026)	(0.034)	(0.034)
Local Bank Controls	N	Y	N	Y
Local Economic Controls	N	Y	N	Y
Demographics Controls	N	Y	N	Y
County FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
N	14,252	14,252	14,252	14,252
R^2	0.561	0.561	0.494	0.495

Table IA.6: **Personal Connections Mitigate Information Frictions**

This table reports results of regressing a loan officer's loan originations on previous work locations and connections with incumbent loan officers at the new work location. *Other county* is an indicator variable that equals one if the new hire loan officer's previous location is in a different county than the new work location and zero otherwise. *Connected* is an indicator variable that equals one if the seasoned loan officer has overlapped past experience with incumbent loan officers in the new branch. In columns (1) and (2), the sample includes all seasoned loan officers externally hired in a year between 2014 and 2022, and overlapped past experience is defined as working in the same company in a previous year according to NMLS. In columns (3) and (4), the sample includes only seasoned loan officers externally hired with a matched user profile in LinkedIn, and overlapped past experience is defined as working in the same company, or attending the same school, in a previous year. The dependent variable in columns (1) and (3) is the natural logarithm of the new hire loan officer's number of loans in the year after hiring. The dependent variable in columns (2) and (4) is the natural logarithm of the loan origination dollar volume in the year after hiring. Loan officer controls include *Experience*, *Male*, and *Minority* for all columns, while the LinkedIn sample includes total years in other industries and number of education records as additional controls. Standard errors, clustered at the county level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Future Mortgage Originations

Connections Based On:	NMLS		LinkedIn	
	Log(Nloans)	Log(Volume)	Log(Nloans)	Log(Volume)
	(1)	(2)	(3)	(4)
Other County × Connected	0.085*	0.080*	0.185**	0.194**
	(0.048)	(0.048)	(0.087)	(0.089)
Other County	-0.136***	-0.156***	-0.216***	-0.244***
	(0.019)	(0.020)	(0.053)	(0.063)
Connected	-0.027	-0.027	-0.021	-0.032
	(0.033)	(0.035)	(0.065)	(0.067)
Controls	Y	Y	Y	Y
Branch × Year FEs	Y	Y	Y	Y
N	43,121	43,121	4,622	4,622
R^2	0.527	0.547	0.553	0.566

Table IA.7: **Movements of Loan Officers Between Counties**

This table reports the estimates of Poisson regressions for the movements of loan officers between counties. Each observation is a county pair-year between 2015 and 2022. The dependent variable is the number of loan officers that move from an origin county to a destination county in a year. *Distance* and *Social Connection* are the number of miles and the Social Connectedness Index between the two counties in a pair. *Lending Connection* is the number of loans that finance a property in the destination county and originated by a loan officer in the origin county in the previous year. Standard errors, two-way clustered at the origin county and destination county levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Number of Relocations

	(1)	(2)	(3)	(4)
Log(Distance)	-1.750***			-0.162***
	(0.055)			(0.039)
Log(Social Connection)		1.441***		0.910***
		(0.018)		(0.038)
Log(Lending Connection)			1.215***	0.364***
			(0.021)	(0.029)
Origin County × Year FEs	Y	Y	Y	Y
Destination County × Year FEs	Y	Y	Y	Y
N	4,690,426	4,690,426	4,690,426	4,690,426