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

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March 2025

Abstract

Using comprehensive data on the locations of loan officers and their loan originations, we find that the majority of the US residential mortgage market remains local, despite developments in financial technology. However, the supply of loan officers is largely unresponsive to local mortgage demand shocks. This lack of responsiveness stems at least in part from asymmetric information about individual productivity, which restricts loan officers' ability to relocate to high-demand locations through the labor market. Remote lending and increased loan officer workloads do not fully substitute for the supply of local loan officers. Our findings suggest that labor immobility can distort local credit supply and reduce capital allocation efficiency.

[†] For helpful comments, we thank David Dicks, Ivy Feng, Joshua Thornton, Jinming Xue, and seminar participants at Baylor University. We are grateful to the Conference of State Bank Supervisors (CSBS) for granting us access to data from NMLS Consumer Access[SM], see https://nmlsconsumeraccess.org/. The results and opinions are those of the authors and do not reflect the position of the CSBS.

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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 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 role played by local information in credit analysis (e.g., Agarwal and Hauswald, 2010), information that is typically acquired by local loan officers.

[Insert Figure 1 Here]

In this paper, we explore the interaction between labor and credit markets, by examining how frictions in the market for loan officers affect lending in local mortgage markets. We do this by combining a new nationwide registry of over 350,000 loan officers with a comprehensive dataset of more than 60 million mortgages that were originated between 2014 and 2022. These data allow us to both measure the productivity of individual loan officers and to track their movements across firms and geographic locations. We thus have a unique window for studying how frictions associated with moving workers between firms and between locations influence local mortgage markets.

We begin by examining how the local supply of loan officers responds to fluctuations in mortgage demand across U.S. counties. The evidence indicates that shocks to the demand for mortgages within counties have only negligible effects on changes in the number of local loan officers. This weak response is documented for both home purchase loans, where demand is proxied by the number of loan applications (Fuster et al., 2019), and for refinance loans,

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

where we isolate variation in demand using the number of existing mortgages predicted to be refinanced in the county, based on the historical stock of mortgages and changes in interest rates.

In addition to showing that loan officers rarely move across counties, we show that the ones who do move tend to be less productive. Within the same branch, seasoned hires from distant locations originate significantly fewer loans than their local counterparts. This productivity gap persists for multiple years after hiring. Importantly, the gap does not exist among seasoned hires with prior work or school ties to the branch's incumbent loan officers, or for loan officers who relocate internally, suggesting asymmetric information about worker productivity, rather than fixed costs of relocation. Overall, these findings point to an adverse selection problem that impedes productive loan officers from moving to locations with increasing mortgage demand.

Given that labor market frictions impede the movements of loan officers across counties, lenders must respond to shocks to mortgage demand in other ways, such as increased loan officer workloads, remote lending, internal relocations, or mortgage pricing. Indeed, we find that loan originations per officer increase with local mortgage demand. In addition, the median distance between the locations of lending officers and the mortgaged properties increases, suggesting that remote lending substitutes for local mortgage supply. In contrast, we find no evidence that lenders internally relocate loan officers or change their pricing in response to local mortgage demand shocks.

We seek to understand whether labor market frictions affect local credit supply. It is possible that the responses by lenders are sufficient, such that these frictions have no effect on the number of mortgages originated in a county. To test whether or not this is the case, we examine whether shocks to the supply of loan officers in a county affect the number of mortgage originations. To avoid omitted variable concerns, we employ an instrumental variables approach where we instrument for the availability of local loan officers.

Our instrument isolates exogenous variation in changes in the number of loan officers by exploiting a county's exposure to changes in lenders' national loan officer workforce. Specifically, we calculate each lender's annual growth rate of loan officers outside the county under consideration. We then aggregate these non-local growth rates to the county level, using the county's exposure share to each lender (based on the lender's number of existing loan officers in the county) as the weight. Our identifying assumption is that the lender-specific growth rates are orthogonal to omitted local shocks. Importantly, labor market frictions lead to these lender-level shocks creating meaningful county-level variation in loan officer growth rates (i.e., a powerful first-stage). We find consistent evidence across OLS and IV specifications: an interquartile increase in the growth of local loan officers (from -11.5% to 10.0%) leads to 14.0% more loan originations and 14.4% greater dollar origination volumes, respectively. This finding indicates that remote lending and increased loan officer workloads do not fully substitute for the supply of local loan officers, hence, local human capital matters for credit supply.

We provide evidence on the channel through which local loan officers affect loan originations by separately examining home purchase and refinance loans. We find that loan officer growth has a larger impact on refinance loans than home purchase loans. This finding likely reflects the fact that demand for home purchase loans is determined by house transactions, which are less sensitive to the number of loan officers in a county, whereas the demand for refinance loans, which can be easily delayed, is likely to be more elastic. In other words, a local market with many loan officers actively reaching out to borrowers is likely to see a larger increase in refinancings than new home purchase mortgages.

In our final set of tests, we explore how the supply of local loan officers affects refinancing efficiency. We find that having local loan officers significantly increases the percentage of local mortgages that are efficiently refinanced (we consider loans to be candidates for efficient refinancing when the national rate is at least 100 basis points lower than the loan's original rate). We find no such effect on loans where the refinancing option is out of the money. The effects on refinancing efficiency are 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.

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), and that the mortgage market is transitioning away from traditional banks toward shadow banks (e.g., Buchak et al., 2018), we document that even during this transition, much of the mortgage market remains local, and lenders' local human capital is an important factor for credit supply.

An important literature in economics documents frictions in labor markets (see Pissarides, 2011 Nobel lecture for a review). Most related to our work are studies documenting adverse selection in labor markets (e.g., Greenwald, 2018), low worker migration rates across geographic regions (e.g., Dahl and Sorenson, 2010), and the role of personal connections/networks in mitigating information frictions in labor markets (e.g., Brown, Setren, and Topa, 2016; Hellerstein, Kutzbach, and Neumark, 2014). We contribute to this literature by using novel micro-data to document these frictions in the loan officer labor market, where we can observe individual workers' productivity across firms and over time. We then provide the first direct evidence on how these labor market frictions affect the supply of mortgage credit. Our findings here add to the nascent literature on capacity constraints in mortgage lending (e.g., Fuster et al., 2019; Choi, Choi, and Kim, 2022).

Finally, our paper 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,[2] 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.

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$^{\text{SM}}$ 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. Third, we link loan officers to their user profiles on LinkedIn. 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] 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), stock market analysts (e.g., Barber et al., 2001; Crane and Crotty, 2020), and financial analysts (e.g., Hwang, Liberti, and Sturgess, 2019).

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.[3] Specifically, we obtain historical snapshots taken at the end of each calendar year from 2012 to 2022 on licenses, registrations, and other information 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.[4] 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.

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. (2024), 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

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

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

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 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. We also use the CoreLogic data to construct a county-year panel (discussed in subsection 2.5) which we use in the county-level analysis.

2.3. 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 two main purposes: (1) to construct our measure for home purchase loan demand following Fuster et al. (2022), and (2) to calculate residualized mortgage interest 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.

2.4. 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 main 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.

2.5. County-year panel

Part 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. 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 2.5% and 97.5% levels.

2.6. Summary statistics

We present summary statistics in Table 1. Panel A reports statistics for variables in our county-year panel between 2015 and 2022.[5] The average loan officer growth rate in a county is around 1.2%. For the average county-year, the loan growth rate is around 17% and 27%, measured by the change in the number of loans and the dollar volume, respectively.

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% of the seasoned hires happen within the same county and the median relocation distance is 9 miles.

[Insert Table 1 Here]

3. Frictions in the loan officer labor market

In this section, we first examine how loan officer supply responds to local mortgage demand shocks. Next, we examine the labor market for loan officers by focusing on the productivity of seasoned loan officers. Lastly, we analyze labor market frictions that impede the movements of loan officers across counties.

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

3.1. Response to local mortgage demand shocks

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, Plosser, Schnabl, and Vickery (2019), by calculating the annual percentage change in the number of home purchase mortgage applications in the county based on HMDA data. The idea is that mortgage application volumes in the United States fluctuate enormously over time, which is primarily driven by macroeconomic 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 that are refinanced within each bin at the national level as probabilities, we calculate the number of existing loans in a county that are predicted to be refinanced.[6]

We first carry out tests to confirm our proxies indeed capture fluctuations in mortgage demand. In Table 2 Panel A column (1), we regress annual percentage change in the number

[6]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.

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 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.

Two potential concerns about our findings could arise. First, our proxies for mortgage demand shocks might be endogenous to the supply of loan officers. If this is the case, this endogeneity would bias us *toward* finding correlations between changes in the loan officer workforce and mortgage demand. However, we do not document such a relationship. Second, instead of adjusting the quantity of loan officers, lenders could improve the quality of these workers 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. Overall, the weak cross-county response of the loan officer workforce to mortgage demand shocks suggests that there are frictions that impede their mobility.

3.2. Labor market for seasoned loan officers

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.[7] However, the distance of relocation is within 20 miles for the vast majority of these job changes (the 75th percentile of *Relocation Distance* is 23.3 miles, as shown in Panel B of Table 1). The fact that most of the seasoned hires are local suggests that, in addition to moving costs, loan officers may face information frictions in the labor market when they move across regions.

We examine productivity for moving loan officers by comparing their post-move mortgage origination volumes to their new coworkers' productivity using our loan officer-year panel. Specifically, we regress the natural logarithm of the number of loans and dollar volume on indicators for the loan officer being a seasoned officer that moved from the same county, or from a different county, respectively. 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.

We present the results in Table 3. Our estimates show that seasoned hires, especially those from a different county, generate fewer loans than incumbent loan officers in the years following their hiring. 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 13% fewer loans than the incumbents, whereas seasoned hires from the same county originate only 2% fewer loans than the incumbents. The F-statistic from a Wald test confirms a statistically

[7] 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.

significant difference between same-county and different-county hires.

[Insert Table 3 Here]

To investigate the persistence of this productivity gap, 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. 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. 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 estimate a non-parametric specification with the same control variables and fixed effects as in Table 3 to provide further evidence of the relationship between seasoned loan officers' post-hiring productivity and the distance of their relocations. Specifically, we group seasoned hires into six bins based on the distance of the move and regress the quantities of loan originations on dummy variables indicating these distance bins.

We present the results in Figure 2. We use origination quantities in the first year after hiring as the outcome variable and plot the regression coefficients for each bin along with the 95% confidence intervals. Our estimates reveal a clear decreasing pattern. The productivity of seasoned hires from the same zip code is indistinguishable from incumbents. However, as the distance of relocation increases, the productivity gap between seasoned hires and incumbents widens. Seasoned hires from within five miles are 10% less productive than incumbents. This gap increases to more than 20% when the distance of relocation is more than 20 miles.[8] These findings suggest that the frictions behind the observed productivity gap are sensitive to even relatively short relocation distances.

[Insert Figure 2 Here]

3.3. Frictions in hiring loan officers

Why are seasoned hires, especially those from distant locations, less productive than incumbent loan officers? We propose an information-based explanation. When making hiring decisions, firms have less information about a candidate's productivity than the candidate themselves or their previous employer. This information asymmetry can give rise to an adverse selection problem in the labor market (e.g., Greenwald, 1986), leading to two consequences. First, relatively less productive loan officers self-select to move to distant locations, consistent with the observed productivity gap. Second, productive loan officers remain in their current locations, which is consistent with the fact that job changes across counties are rare overall.

In this subsection, we provide evidence consistent with this adverse selection problem. We do so by exploring two settings in which the information asymmetry between firms and candidates is reduced: cases where seasoned hires have prior connections to workers at the hiring branch, and cases where loan officers relocate internally (within the firm).

3.3.1. Connected hires

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

[8] We find similar patterns when measuring productivity with loan originations in the second and third years after hiring.

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.

We present the results in Table 4. In 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. The coefficients of interest are the interaction terms between *Connected* and *Other County*. Using column (1) as an example, we find a positive and statistically significant coefficient when using the natural logarithm of the number of loans as the outcome variable. This finding is also economically meaningful: among loan officers hired from other counties, connected hires originate 9% more loans than unconnected ones. In addition, the sum of the coefficients on *Connected* and the interaction term is statistically significantly different from zero at the 1% level. In sum, the results are consistent with the notion of asymmetric information in the seasoned loan officer market; that is, personal connections could alleviate this problem.

[Insert Table 4 Here]

In columns (3) and (4), we refine our measure of personal connections by restricting the sample to loan officers matched with LinkedIn profiles and set *Connected* to include any overlapping work or education experience in LinkedIn. The LinkedIn-matched sample allows us to observe personal ties based on education and work history outside of the mortgage industry that are not available in the NMLS data. We find consistent, if not stronger, results. For example, in column (3), we find that connected hires from a different county originate 21% more loans than unconnected ones. In columns (2) and (4), we replace the outcome variable, the natural logarithm of the number of loans, with the natural logarithm of dollar volumes, and find similar results.

Moreover, if relocation were to mechanically reduce any loan officer's productivity in the short term, loan officers hired from other counties would become less productive even if they have personal connections. However, our estimates show that among connected hires (i.e., removing the potential information asymmetry issue), loan officers originate similar quantities of loans, regardless of whether they come from the same or a different county. We test the joint statistical significance of the coefficients on *Other County* and the interaction term and find it is indistinguishable from zero. This result provides evidence that fixed relocation costs do not drive our findings.[9]

In addition, we compare loan officers' past loan originations and present the results in Table IA.2. In Panel A, we find that loan officers who originated more loans than peers in the same branch and year in the past are more likely to change jobs within the same county, whereas those who originated fewer loans are more likely to move to a different county.[10] In Panel B, we also sharpen this test by restricting the sample to loan officers who change jobs in the next year. Our results suggest that for two officers who worked in the same branch and moved at the same time, the less productive officer is more likely to move farther away. Together, the results suggest that when changing jobs, productive loan officers tend to stay in their current locations, whereas less productive loan officers tend to relocate.

Overall, 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

[9]One potential concern is that our personal connection measures also capture social connections in general (Bailey et al., 2018). We carry out a horse race between our measures of personal connection, social connection, and moving distance, all interacted with *Other County*, and present the results in Table IA.3. We find that the coefficient on the interaction between personal connection and *Other County* remains similar to the results in Table 4, whereas the interaction terms between social connection and *Other County* as well as between distance and *Other County* are economically small and statistically insignificant. These results provide further evidence that our findings are capturing the effect of information asymmetry about loan officer quality and adverse selection, rather than alternative mechanisms.

[10]In Figure IA.2, we sort seasoned loan officers' relocation distance into six bins. We find consistent evidence that less productive loan officers are more likely to move a longer distance.

prevent productive loan officers from moving between institutions.

3.3.2. Internal relocation

Given that the adverse selection problem stems from information asymmetry between lenders and seasoned hires, internally relocated loan officers should be less likely to face this issue. For these existing employees, lenders already have a reasonable understanding of their productivity. We examine the productivity of internally relocated loan officers using tests similar to Table 3. Specifically, we regress loan officers' future origination quantities on *Internal Relocate*, an indicator variable that equals one if the loan officer is internally relocated to a different county and zero otherwise. Our sample excludes externally hired loan officers. Hence, we compare internally relocated workers to incumbent workers at the branch they join.

We present the results in Table 5. In columns (1) to (3), we focus on the number of loans that the loan officer originates in the first, second, and third years after hiring, respectively. Comparing two loan officers from the same branch and year (through branch times year fixed effects), we find an economically small and statistically insignificant difference between an internally relocated loan officer and an incumbent's productivity. The results remain similar when we use dollar volume of loan originations as the dependent variable in columns (4) to (6).

[Insert Table 5 Here]

We also test for potential selection in internal relocation. We use the same approach as in Table IA.2 and compare the *past* productivity of internally relocating loan officers to loan officers from the same branch and year. Our results in Table IA.4 suggest limited productivity-based selection in internal relocation: loan officers who are relocated internally have comparable (or marginally higher) past productivity compared to their peers in the same branch.

Overall, our findings support the idea that internally relocated loan officers are less likely to suffer from the potential adverse selection problem. The contrast between these results and previous findings for external hires provides further evidence of the information friction between lenders and external loan officers.

4. Lender response to mortgage demand shocks

In this section, we explore several ways that lenders might substitute/adjust for the lack of local human capital when labor market frictions impede the movement of loan officers across counties. First, we examine loan officer workloads. Second, we study the substitution between local and remote lending. Third, we examine whether lenders relocate loan officers internally or adjust mortgage interest rates.

4.1. Loan officer workload

Faced with high demand for mortgages and labor market frictions, lenders might increase the workload per officer, i.e., assign each loan officer more loans to handle. We test this hypothesis and present the results in Table 6. Columns (1)-(2) and (3)-(4) focus on home purchase and refinance loans, respectively. We regress the change in the number of loans *per officer* on the proxies for changes in mortgage demand, along with local bank controls, local economic controls, demographics controls, county fixed effects, and year fixed effects.

[Insert Table 6 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 54% increase in loan officer workload. The effects are slightly larger for refinance loans: doubling refinance loan demand leads to a 72% increase in loan officer workload. If increasing the workload of the existing loan officers could fully absorb 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 cannot fully absorb shocks to demand.

4.2. 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 examine the median lending distances for home purchase and refinance loans (measured as the distance between the property and the loan officer's work location). We test whether lending distances increase in response to mortgage demand shocks. Table 7 presents the results for home purchase and refinance loans in columns (1)-(2) and (3)-(4), respectively.

[Insert Table 7 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 12-mile increase in median lending distance. The results are much larger in magnitude for refinance loans: doubling refinance loan demand increases the median distance by more than 100 miles. Together, this evidence suggests that substitution from local to remote lending could partially mitigate the effects of frictions in the loan officer labor market. Our subsequent tests estimating the effects on lending activity suggest this substitution is far from complete.

4.3. Internal relocation and loan pricing

Lastly, we explore whether lenders respond to increased mortgage demand in certain areas by relocating loan officers internally or adjusting mortgage rates. Previous results documented that internal relocations do not suffer from the same adverse selection issues that characterize external hires. Hence, lenders might use relocations as a tool to handle local spikes in mortgage demand. Following the same approach as in preceding tables, in Table IA.5, we show that shocks to local mortgage demand do not have a statistically or economically significant effect on the number of loan officers in a county due to internal relocations. These findings suggest that even though internal relocations can be helpful in addressing labor market frictions, they are not widely adopted in practice. In fact, internal relocations are rare, accounting for less than 3% of all hires or moves in the data.

Alternatively, 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.6. 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.

5. The impact of local human capital on mortgage lending

Collectively, the responses documented in the previous section 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 of labor market frictions on local mortgage markets. However, we find that this is not the case.

In this section, we directly examine the importance of human capital for the supply of financial capital using our county-year panel. We start by establishing a positive relationship between the number of loan officers in a county and the number of mortgage originations. We then leverage an instrumental variables approach to isolate exogenous variation in the number of local loan officers. Next, we 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 affect the efficiency of local borrowers' mortgage refinancing decisions.

5.1. Loan officers and mortgage originations

We start by showing that the growth rate of local loan officers affects mortgage origination volume. Using our county-year panel, we run OLS regressions of the changes in loan originations on the changes in the number of loan officers and present the results in Table 8. In columns (1) and (2), we focus on the changes in the number of loans (i.e., $\Delta NLoans$) as the dependent variable. Column (1) presents the regression results with county and year fixed effects. We find a positive and statistically significant relationship between loan officer growth and loan volume. 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. The coefficient of interest remains virtually unchanged. In columns (3) and (4), we replace the dependent variable with the change in total loan dollar volume (i.e., $\Delta \$ Volume$) and find similar results.

[Insert Table 8 Here]

The OLS estimates with granular fixed effects and tight controls provide suggestive evidence that local loan officer growth boosts local originations. However, these tests suffer from potential endogeneity concerns as loan officer growth could be correlated with mortgage demand. For example, banks may recruit more loan officers in a county when the county's mortgage demand surges. As such, unobserved local demand not captured by the control variables could lead to a positive relationship between loan officer growth and loan originations, even if there is no underlying causal relationship. In the next subsection, we use an instrumental variables approach to address this concern.

5.2. Instrumental variables approach

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, $\textit{LO Growth Exposure}_{c,t}$, 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 driven by local mortgage demand. 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.7. If our IV isolates variation in loan officer growth that is unrelated to local mortgage demand, it should not correlate with proxies for mortgage market demand shocks. Indeed, we find little evidence for such a correlation between our instrument and proxies for mortgage demand shocks. In Table IA.7 columns (1) and (3), we separately regress the instrument on the changes in demand for home purchase and refinance loans, respectively, and find statistically insignificant and economically small coefficients. In column (5), we include both proxies for mortgage demand in the same regression and continue to find coefficients that are indistinguishable from zero. Columns (2), (4), and (6) of Table IA.7 report regressions of our instrument on the covariates and find little-to-no correlation between the instrument and observable characteristics. Overall, these covariate balance tests provide support for the exclusion restriction and our instrumental variables approach.

We present our IV results in Table 9. 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 just over 100, suggesting a strong instrument.

[Insert Table 9 Here]

In columns (3) to (6), we carry out the same analysis as in Table 8, but using the two-stage least squares approach. We focus on the changes in the number of loans (i.e., $\Delta NLoans$) and total loan dollar volume (i.e., $\Delta\$Volume$) as the dependent variables in columns (3)-(4) and (5)-(6), respectively. We find causal evidence that is qualitatively similar to the OLS results and supports the hypothesis that loan officer growth increases local loan originations. 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 dollar origination volumes, respectively.

5.3. Heterogeneous effects on home purchase and refinance loans

In this subsection, 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 human capital is important. 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.

We present the results across loan types in Table 10. 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 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 60%–100% 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.

[Insert Table 10 Here]

5.4. Effects on the efficiency of mortgage refinancing

In our final set of tests, we explore how the supply of local loan officers affects refinancing efficiency. Using data from Fannie Mae and Freddie Mae, we label 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 label 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 candidates and inefficient candidates.

In Table 11, 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.[11]

[Insert Table 11 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).

[11] We estimate loan-level NPV from refinancing existing mortgages using GSE data. In Figure IA.3, we present the distribution of the NPVs.

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 frictions in the labor market for loan officers affect 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. We find that loan officers who move across counties tend to be less productive, except for seasoned hires with prior work or school ties to the branch's incumbent workers, or for loan officers who relocate internally. These findings point to asymmetric information about a distant loan officer's productivity, which gives rise to an adverse selection problem. This labor market friction impedes productive loan officers from moving to locations with increasing mortgage demand.

We find that lenders' local human capital has a significant effect on the number of mortgages originated in a county, suggesting that labor market frictions play an important role in local credit supply. The effects come primarily from refinance loans rather than home purchase loans, as home purchase loans are tied to housing transactions and are largely inelastic to loan officers in a county, whereas refinance loans are flexible and can be delayed. Our findings suggest that labor market frictions and human capital constraints likely contribute to the overall lack of refinancing activity by U.S. households.

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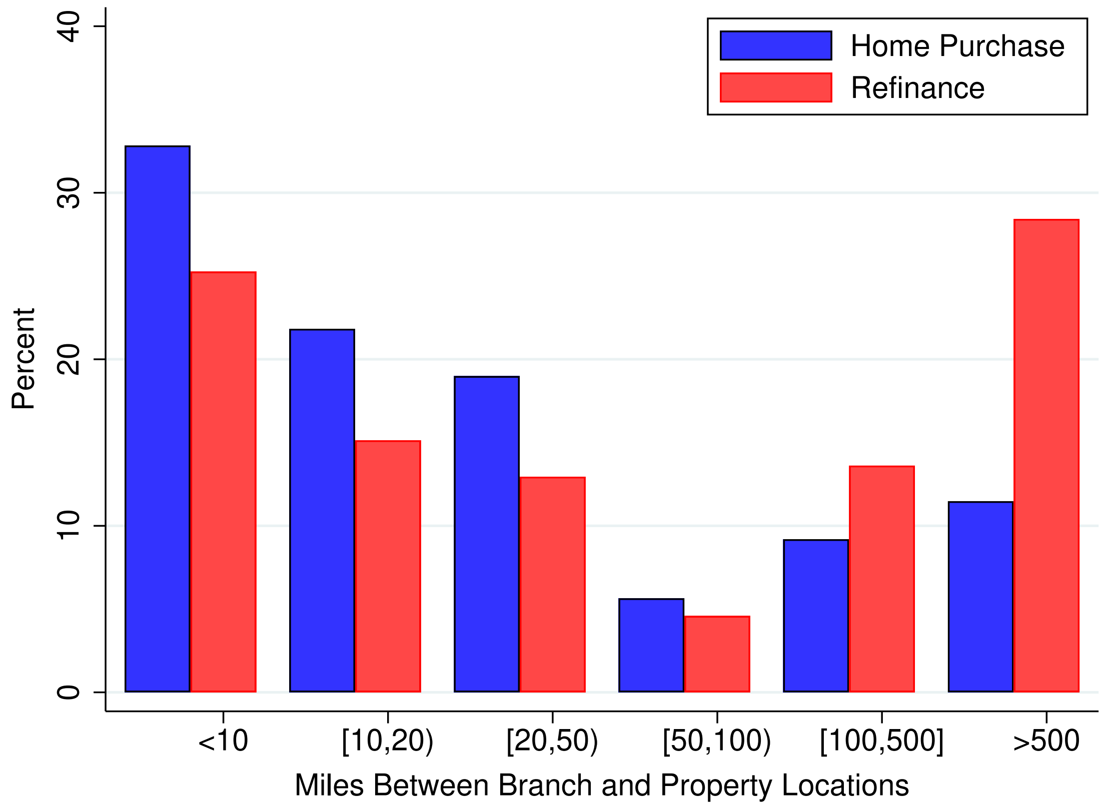

Figure 1: **Lending Distance in the US Residential Mortgage Market: 2014–2022** This figure presents the lending distance of 62 million US mortgage loans originated between 2014–2022 by loan purpose. Lending distance is measured as the straight line distance (in miles) between the property location and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

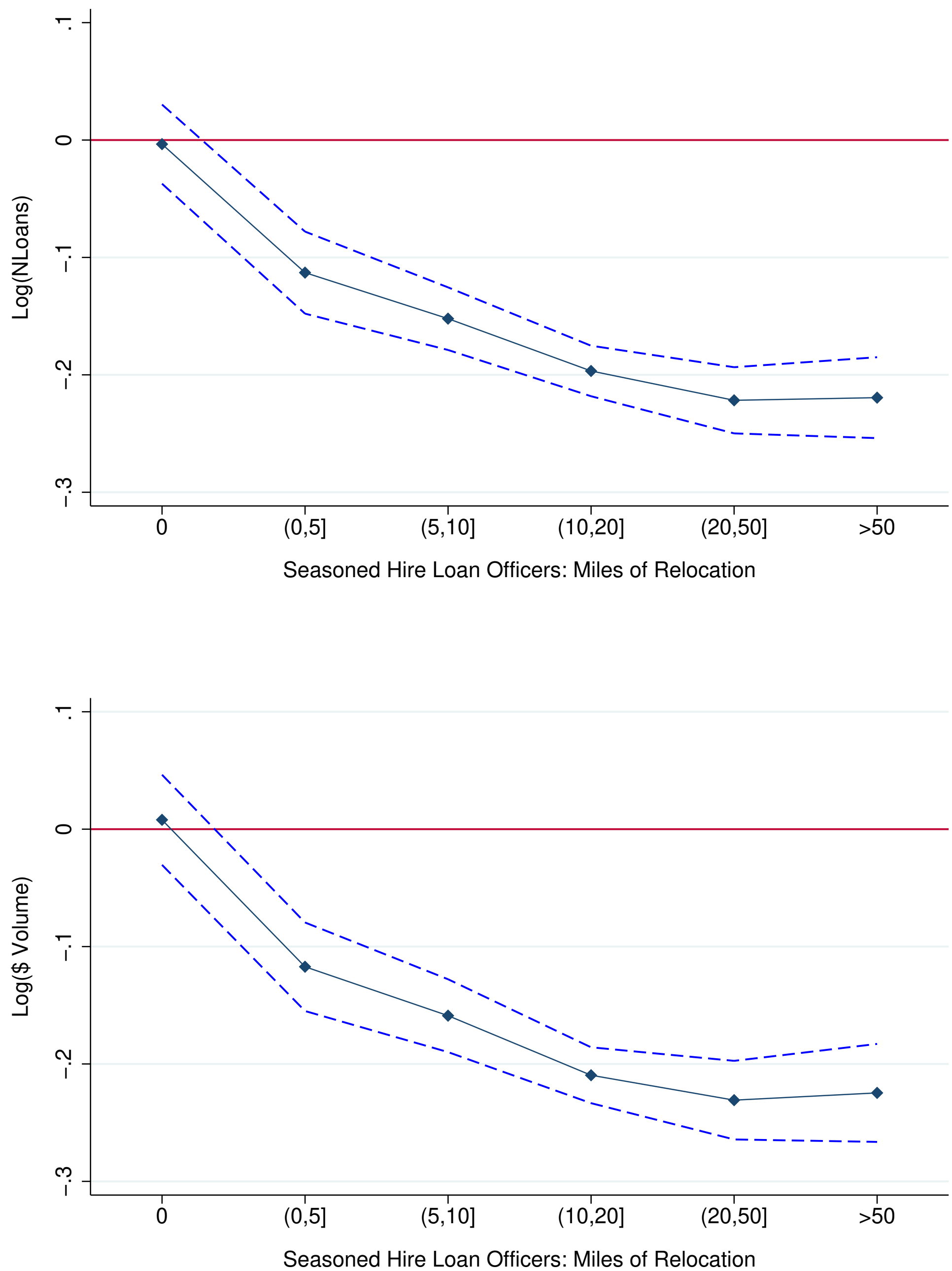

Figure 2: **Distance of Loan Officer Relocation and Post-Hiring Productivity**
This figure presents non-parametric estimates for the relationship between a seasoned loan officer's relocation distance and post-hiring productivity in the number of loans and dollar volume relative to existing loan officers in the branch, in the top and bottom panels, respectively. Control variables and fixed effects are the same as in Table 3. Dashed lines represent 95% confidence intervals. Standard errors are clustered at the county 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 (1)	Mean (2)	SD (3)	P25 (4)	P50 (5)	P75 (6)
ΔLO	14,292	1.2%	23.5%	-11.5%	0.0%	10.0%
ΔDemand: Purchase	14,292	5.4%	16.0%	-4.2%	5.4%	14.2%
ΔDemand: Refi	14,292	18.9%	66.9%	-23.3%	2.3%	40.3%
ΔNloans	14,292	17.4%	67.3%	-9.8%	5.3%	23.2%
Δ$Volume	14,292	27.3%	84.3%	-8.6%	10.6%	35.8%
ΔNloans: Purchase	14,292	15.8%	50.4%	-5.0%	5.6%	17.3%
Δ$Volume: Purchase	14,292	24.2%	55.4%	0.3%	12.5%	27.1%
ΔNloans: Refi	14,292	23.2%	77.2%	-23.3%	4.0%	45.5%
Δ$Volume: Refi	14,292	33.4%	93.2%	-24.3%	7.2%	65.5%
ΔNloans per LO: Purchase	14,292	18.8%	50.7%	-7.0%	6.9%	26.7%
ΔNloans per LO: Refi	14,292	24.9%	77.4%	-25.5%	4.1%	53.5%
Lending Distance: Purchase	14,292	63.7	74.2	27.5	44.2	72.2
Lending Distance: Refi	14,292	219.0	310.0	35.8	77.1	253.2
LO Growth Exposure	14,292	-0.7%	15.5%	-9.3%	-0.9%	6.5%
Refi Nloans%: Δrate <-100 bps	14,282	18.6%	8.7%	12.7%	16.0%	25.0%
Refi $Volume%: Δrate <-100 bps	14,282	20.3%	10.0%	13.3%	16.9%	28.0%
Refi Nloans%: Δrate >+100 bps	11,501	6.3%	9.4%	0.0%	5.7%	8.0%
Refi $Volume%: 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 (1)	Mean (2)	SD (3)	P25 (4)	P50 (5)	P75 (6)
All Loan Officer-Year:						
Nloans: Year 1	1,173,850	40.4	62.5	5.0	19.0	51.0
Nloans: Year 2	915,229	42.5	64.5	6.0	21.0	55.0
Nloans: Year 3	711,311	44.2	66.3	6.0	22.0	57.0
$Volume: Year 1	1,172,862	11.3	24.5	0.9	4.4	13.3
$Volume: Year 2	914,398	12.3	25.5	1.1	5.1	14.6
$Volume: Year 3	710,585	13.1	26.9	1.2	5.6	15.7
Internal Relocate	1,486,241	0.007	0.085	0.000	0.000	0.000
Experience	1,639,301	2.590	2.306	1.000	2.000	4.000
Male	1,639,301	0.566	0.496	0.000	1.000	1.000
Minority	1,639,301	0.110	0.313	0.000	0.000	0.000
Seasoned Hire Loan Officer-Year:						
Relocation Distance	119,210	99.0	319.3	1.9	8.7	23.3
Same County	119,210	0.60	0.49	0.00	1.00	1.00
Other County	119,210	0.40	0.49	0.00	0.00	1.00
Connected: NMLS	119,210	0.05	0.23	0.00	0.00	0.00
Connected: LinkedIn	16,412	0.14	0.35	0.00	0.00	0.00

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 results of regressing 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	0.566***	0.555***		
	(0.028)	(0.028)		
ΔDemand: Refi			1.324***	1.329***
			(0.056)	(0.055)
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	0.498	0.499	0.968	0.969

Panel B: Change in Number of Loan Officers

	Purchase		Refi	
	(1)	(2)	(3)	(4)
ΔDemand: Purchase	0.030	0.027		
	(0.021)	(0.021)		
ΔDemand: Refi			0.001	0.018
			(0.063)	(0.063)
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: **Adverse Selection in the Labor Market for Loan Officers**

This table reports results 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 2014 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. *Same County* is an indicator variable that equals one if the seasoned loan officer's previous work location is in the same county as the new work location. *Other County* is an indicator variable that equals one if the seasoned loan officer's previous work location is in a different county than the new work location. These dummies equal zero for existing loan officers. Control variables include *Experience*, *Male*, and *Minority*. The F-statistics and p-values reported at the end of the table test the difference between *Same County* and *Other County*. 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

	Log(Nloans)			Log($Volume)		
	Year 1	Year 2	Year 3	Year 1	Year 2	Year 3
	(1)	(2)	(3)	(4)	(5)	(6)
Same County	-0.024*	-0.026*	-0.026	-0.020	-0.021	-0.027
	(0.014)	(0.015)	(0.016)	(0.016)	(0.017)	(0.018)
Other County	-0.133***	-0.102***	-0.079***	-0.129***	-0.100***	-0.081***
	(0.012)	(0.015)	(0.015)	(0.014)	(0.018)	(0.018)
Experience	0.211***	0.202***	0.206***	0.252***	0.241***	0.245***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Male	0.073***	0.069***	0.063***	0.150***	0.148***	0.142***
	(0.008)	(0.009)	(0.010)	(0.010)	(0.010)	(0.011)
Minority	-0.017	-0.019	-0.021	-0.093***	-0.094***	-0.097***
	(0.011)	(0.013)	(0.014)	(0.012)	(0.014)	(0.016)
Branch × Year FEs	Y	Y	Y	Y	Y	Y
N	818,601	613,651	456,278	818,601	613,651	456,278
R^2	0.519	0.500	0.489	0.597	0.578	0.563
F-statistic	55.0	25.9	8.2	49.8	24.1	7.4
p-value	0.000	0.000	0.004	0.000	0.000	0.006

Table 4: **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 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 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	0.087**	0.080*	0.207**	0.210**
	(0.044)	(0.044)	(0.081)	(0.083)
Other County	-0.133***	-0.150***	-0.194***	-0.210***
	(0.018)	(0.019)	(0.045)	(0.054)
Connected	-0.009	-0.012	-0.019	-0.022
	(0.033)	(0.034)	(0.062)	(0.064)
Controls	Y	Y	Y	Y
Branch × Year FEs	Y	Y	Y	Y
N	49,177	49,177	5,485	5,485
R^2	0.517	0.540	0.544	0.558

Table 5: **Internal Relocations Avoid Information Frictions**

This table reports results of regressing a loan officer's loan originations on a dummy indicating the internal relocation of loan officers. The sample includes all loan offices in NMLS between 2014 and 2022, excluding seasoned (outside) hire in the year. *Internal Relocate* is an indicator variable that equals one if the seasoned loan officer is employed by the same firm but only changing job location to a branch located in a different county. In columns (1) to (3), the dependent variable is the natural logarithm of a loan officer's number of loan originations in the next first, second, and third years, respectively. In columns (4) to (6) we replace the dependent variable with the natural logarithm of a loan officer's annual loan origination dollar volume. Loan officer controls 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: 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)
Internal Relocate	-0.003	-0.004	-0.033	-0.006	-0.000	-0.049
	(0.024)	(0.028)	(0.029)	(0.025)	(0.029)	(0.030)
Controls	Y	Y	Y	Y	Y	Y
Branch × Year FEs	Y	Y	Y	Y	Y	Y
N	738,920	549,138	405,005	738,920	549,138	405,005
R^2	0.529	0.512	0.502	0.608	0.589	0.576

Table 6: **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	0.550***	0.544***		
	(0.039)	(0.038)		
ΔDemand: Refi			0.754***	0.723***
			(0.138)	(0.142)
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	0.319	0.321	0.519	0.521

Table 7: **Mortgage Demand Shocks and Median Lending Distance**

This table reports estimates from regressing the median lending distance of mortgages (miles) 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: Median Lending Distance

	Purchase		Refi	
	(1)	(2)	(3)	(4)
ΔDemand: Purchase	11.606**	11.785***		
	(4.506)	(4.436)		
ΔDemand: Refi			116.510**	101.996**
			(49.278)	(49.625)
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	0.763	0.763	0.804	0.805

Table 8: **Local Loan Officers and Mortgage Originations—OLS**

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		Δ$Volume	
	(1)	(2)	(3)	(4)
ΔLO	0.419***	0.419***	0.494***	0.494***
	(0.036)	(0.036)	(0.047)	(0.047)
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	0.763	0.763	0.804	0.805

Table 9: **Local Loan Officers and Mortgage Originations—IV**

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: Mortgage Originations

	First Stage		Second Stage			
	ΔLO		ΔNLoans		Δ$Volume	
	(1)	(2)	(3)	(4)	(5)	(6)
LO Growth Exposure	0.205***	0.204***				
	(0.019)	(0.020)				
ΔLO			0.653***	0.653***	0.677***	0.675***
			(0.186)	(0.187)	(0.237)	(0.238)
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	0.183	0.185				
F-statistic	110.3	108.6				

Table 10: **Local Loan Officers and Mortgage Originations—By Loan Type**

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.

Second Stage Dependent Variable: Mortgage Originations

	ΔNLoans		Δ$Volume	
	Purchase	Refi	Purchase	Refi
	(1)	(2)	(3)	(4)
ΔLO	0.258*	0.424**	0.230	0.463**
	(0.135)	(0.167)	(0.155)	(0.216)
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	108.6	108.6	108.6	108.6

Table 11: **The 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 either 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.

Second Stage Dependent Variable: Fraction Refinanced

	NLoans%		$Volume%	
ΔRate of existing loans:	<-100 bps	>+100 bps	<-100 bps	>+100 bps
	(1)	(2)	(3)	(4)
ΔLO	0.025**	-0.029	0.031**	-0.021
	(0.013)	(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	109.6	90.2	109.6	90.2

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.
$\Delta\$$Volume	Percentage changes in the dollar volume (million USD) of mortgage loan originations in the county.
Lending Distance	The median distance (miles) between the loan officer's branch location and the property's location.
LO Growth Exposure	The county's exposure to lender-level loan officer growth in other counties.
Refi Nloans%	The fraction of existing mortgages in the county refinanced during the year, based on the number of loans.
Refi \$Volume%	The fraction of existing mortgages in the county that are refinanced during the year, based on the dollar volumes.
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.
Internal Relocate	An indicator variable that equals one if the loan officer is relocated to the current branch from the same firm's branch located in a different county.
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
Relocation Distance	The distance (miles) between the seasoned hire loan officer's former and current branches.
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
Connected: NMLS	An indicator that equals one if the seasoned hire loan officer has overlapped past experience in the same branch-year with incumbent loan officers based on NMLS data.
Connected: LinkedIn	An indicator that equals one if the seasoned hire loan officer has overlapped past experience in the same company-year or the same school-year with incumbent loan officers based on LinkedIn data.

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

Internet Appendix

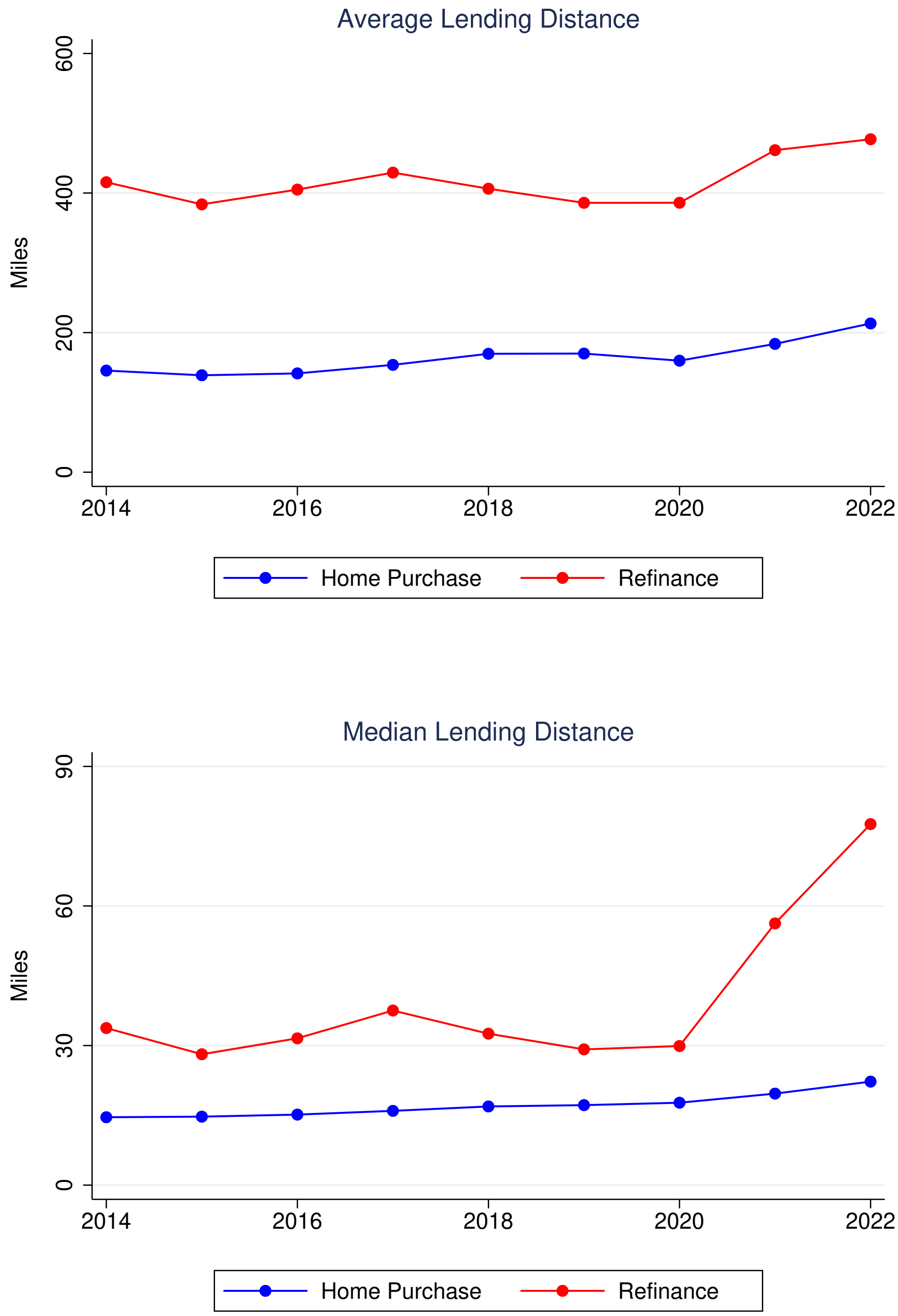

Figure IA.1: **Lending Distance: Time Trend 2014–2022.**
This figure presents annual average lending distances by loan purpose and year. Lending distance is measured as the straight line distance (in miles) between the property location and the origination loan officer's branch location, both at the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

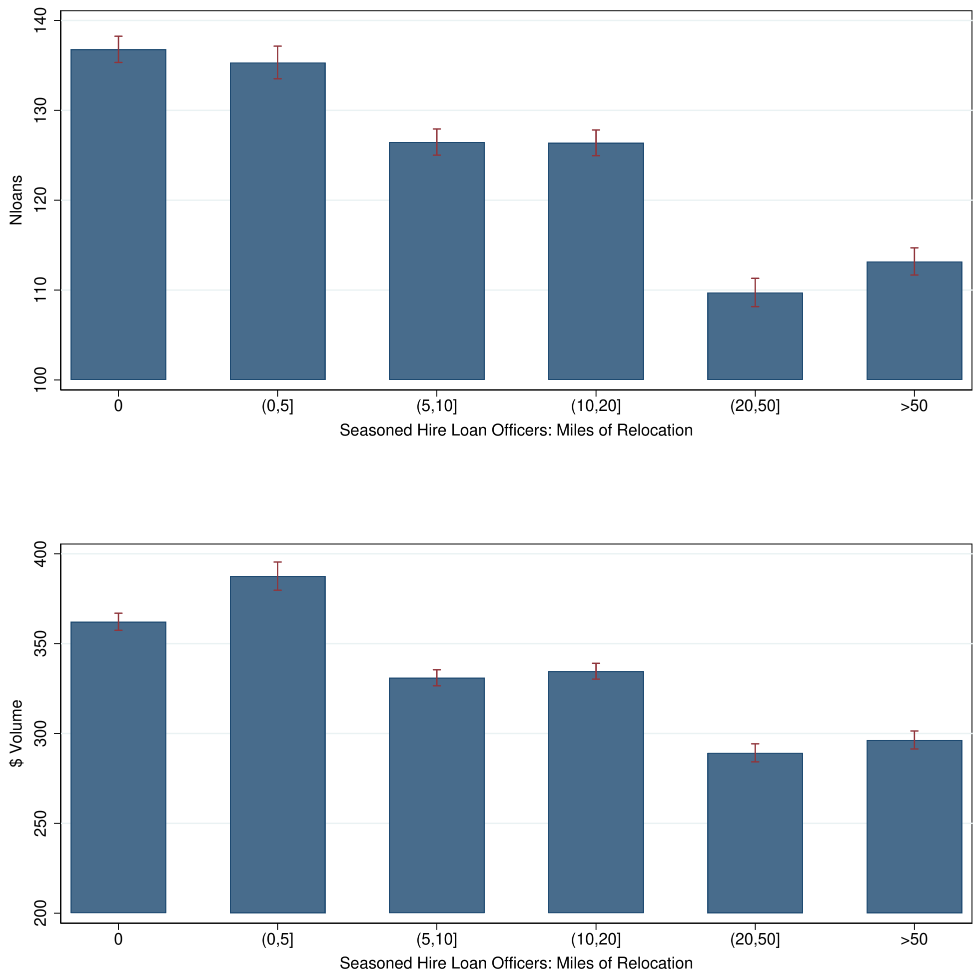

Figure IA.2: **Distance Of Loan Officer Relocation and Past Productivity.**
This figure plots the average relocation distance for seasoned loan officers in bins and total loan originations over the last three years. We measure loan origination using the number of loans and dollar volume, in the top and bottom panels, respectively.

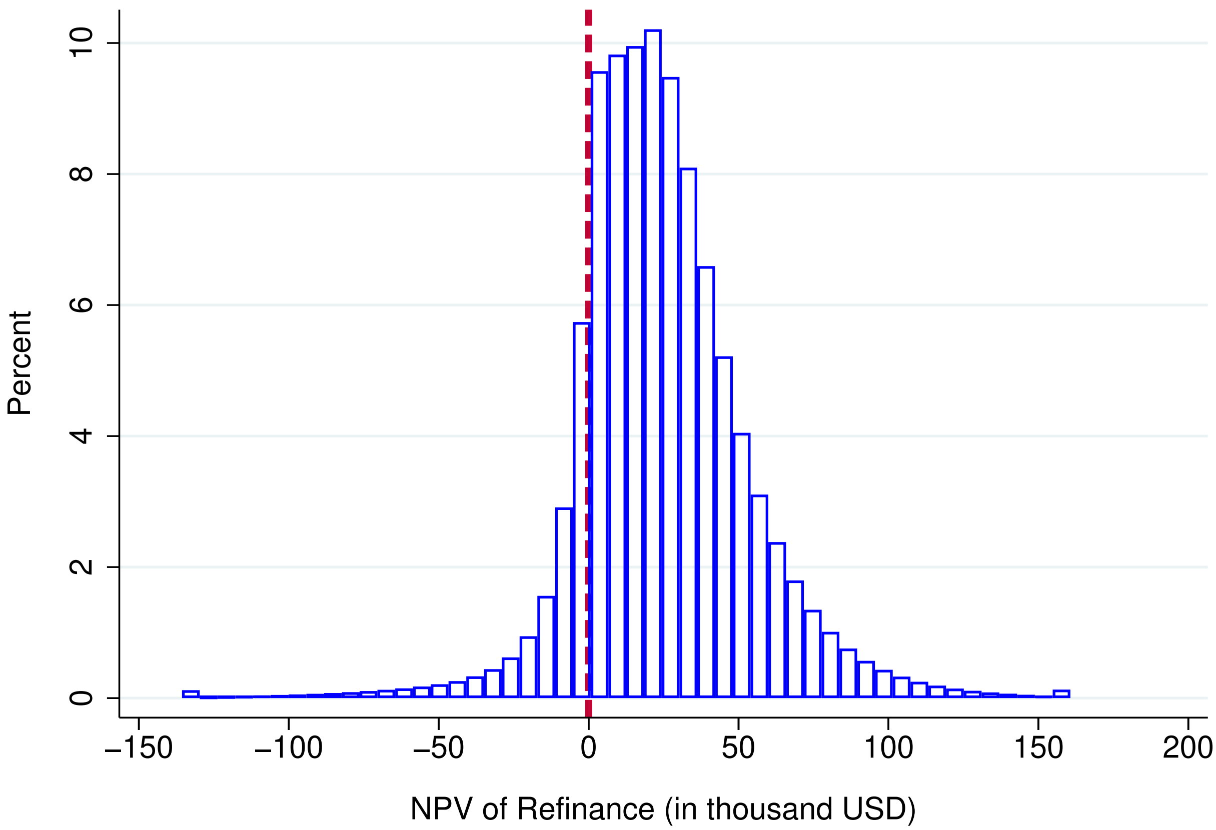

Figure IA.3: **Distribution of NPV from Refinancing Existing Mortgages**
This figure presents the distribution of NPV from refinancing existing mortgages. The sample includes all prepayment events of mortgages in Fannie Mae and Freddie Mac with at least a $70,000 remaining balance between 2012–2022. 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	-0.015	-0.017		
	(0.047)	(0.047)		
ΔDemand: Refi			-0.308**	-0.305**
			(0.142)	(0.141)
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: **Seasoned Loan Officers' Past Productivity and Distance of Relocation**

This table reports results of regressing indicator variables for a loan officer's new job location on total loan originations over the last three years. In Panel A, the sample includes all loan officers in NMLS between 2016 and 2022. In columns (1) and (2), the dependent variable is a dummy variable that equals one if the loan officer takes a new job in the same county, and in columns (3) and (4), the dependent variable is a dummy variable that equals one if the loan officer takes a new job in a different county. In Panel B, the sample includes only loan officer years in which a job change occurs. In columns (1) and (2), the dependent variable is a dummy variable that equals one if the loan officer takes a new job in a different county. In columns (3) and (4), the dependent variable is the natural logarithm of the distance of the move. 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.

Panel A: Unconditional Sample

	Same County		Other County	
	(1)	(2)	(3)	(4)
Past Log(NLoans)	0.006***		-0.000	
	(0.000)		(0.000)	
Past Log($Volume)		0.005***		0.000
		(0.000)		(0.000)
Controls	Y	Y	Y	Y
Branch × Year FEs	Y	Y	Y	Y
N	553,746	553,746	553,746	553,746
R^2	0.471	0.471	0.318	0.318

Panel B: Conditional on Move

	Other County		Log(Distance)	
	(1)	(2)	(3)	(4)
Past Log(NLoans)	-0.029***		-0.123***	
	(0.004)		(0.018)	
Past Log($Volume)		-0.028***		-0.115***
		(0.004)		(0.019)
Controls	Y	Y	Y	Y
Branch × Year FEs	Y	Y	Y	Y
N	25,539	25,539	25,539	25,539
R^2	0.615	0.615	0.656	0.656

Table IA.3: **Personal Connections versus Social Connections**

This table reports results of re-estimating regressions in Table 4, and all specifications additionally include interaction terms between *Other county* and measures of social connections between a seasoned hire loan officer's previous and current counties. *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 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 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. Controls include *Other county* and *Connected*, as well as the loan officer's *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*	0.077*	0.207**	0.210**
	(0.044)	(0.045)	(0.082)	(0.084)
Other County × Log(SCI)	0.007	0.002	0.019	0.014
	(0.017)	(0.020)	(0.053)	(0.056)
Other County × Log(Distance)	-0.009	-0.016	-0.010	-0.018
	(0.016)	(0.018)	(0.054)	(0.054)
Controls	Y	Y	Y	Y
Branch × Year FEs	Y	Y	Y	Y
N	49,177	49,177	5,485	5,485
R^2	0.517	0.540	0.544	0.559

Table IA.4: **Loan Officers' Past Productivity and Internal Relocation**

This table reports estimates from regressing an indicator variable for internal relocation on a loan officer's total loan originations over the last three years. The sample includes all loan officers in NMLS between 2016 and 2022. The dependent variable is an indicator variable that equals one if the seasoned loan officer is employed by the same firm but only changing job location to a branch located in a different county. 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: Internal Relocation

	(1)	(2)	(3)	(4)
Past Log(NLoans)	0.001***	0.001***		
	(0.000)	(0.000)		
Past Log($Volume)			0.001***	0.001***
			(0.000)	(0.000)
Controls	N	Y	N	Y
Branch × Year FEs	Y	Y	Y	Y
N	648,408	553,746	648,408	553,746
R^2	0.327	0.334	0.327	0.334

Table IA.5: **Mortgage Demand Shocks and Internal Relocation of Loan Officers**

This table reports results of regressing the percentage change in loan officers in a county due to internal relocations 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: Change via Internal Relocation

	Purchase		Refi	
	(1)	(2)	(3)	(4)
ΔDemand: Purchase	-0.000	-0.000		
	(0.000)	(0.000)		
ΔDemand: Refi			-0.001	-0.002
			(0.004)	(0.004)
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	0.238	0.239	0.238	0.239

Table IA.6: **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.7: **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 the county's exposure to firm-level loan officer growth in other local markets. 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	0.000	0.000			0.000	-0.000
	(0.011)	(0.011)			(0.011)	(0.011)
ΔDemand: Refi			-0.021	-0.016	-0.021	-0.017
			(0.037)	(0.038)	(0.037)	(0.038)
Local bank controls						
ΔNbranches		0.010		0.010		0.010
		(0.033)		(0.033)		(0.033)
ΔDeposits		0.056**		0.056**		0.056**
		(0.026)		(0.026)		(0.026)
ΔSmallBankShare		0.025		0.025		0.025
		(0.030)		(0.030)		(0.030)
ΔHHI(Branches)		-0.013		-0.012		-0.012
		(0.141)		(0.142)		(0.142)
Local economic controls						
ΔIncome		0.045		0.043		0.044
		(0.052)		(0.052)		(0.052)
ΔUnemployment		0.001		0.001		0.001
		(0.002)		(0.002)		(0.002)
ΔHouseIndex		0.036		0.036		0.036
		(0.038)		(0.038)		(0.038)
Demographics controls						
ΔPopulation		-0.096		-0.096		-0.096
		(0.148)		(0.148)		(0.148)
ΔWhiteShare		0.120		0.121		0.121
		(0.857)		(0.857)		(0.857)
ΔBachelorShare		-0.050		-0.048		-0.049
		(0.190)		(0.190)		(0.190)
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	0.275	0.275	0.275	0.275	0.275	0.275