Mortgages Originated by Amateur Loan Officers: Consequences for Loan Performance and the Housing Cycle

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September 16, 2022

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Abstract

This paper studies the impacts of lending officers' experience on loan performance and the housing market cycles. Using the matched dataset of individual loan officer- and mortgage performance-level data from 2018 to 2021, I find that the mortgage delinquency rate decreases with the lending officer's year of experience at origination. Moreover, due to the imperfect screenings, a mass entry of inexperienced loan officers has an aggregate impact on the housing market: counties in states with more inflows of new loan officers face more rapid home price growths. Finally, motivated by the empirical findings, I build a partial equilibrium model of the lending amount decision of a bank. Counterfactual experiments suggest that policies that limit the entry of new loan officers and intensify training programs for newcomers can significantly reduce adverse outcomes in the market.

JEL Classification: G21, G28, R51, E32

Keywords: Loan Officer Experience, Mortgage Lending, Mortgage Delinquency, Housing Cycle

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1 Introduction

It has been widely accepted that the US housing market exhibits cyclical patterns (Kaplan et al., 2020). For example, according to a well-known narrative about the Great Recession (Mian et al., 2013; Mian and Sufi, 2009, 2014), the market had experienced a sustained housing boom for years, and then started to collapse, triggering a global financial crisis. What has been rarely highlighted behind this cyclical pattern is that the booms and busts in home prices are often accompanied by huge increases and drops in lending officer employment. Figure 1 demonstrates the close relationship between house prices and loan officer employment. Loan officer employment grew considerably with the rise in house prices, during both the pre-crisis period (i.e., 2003–2006) and the recent housing boom since 2019.

[Figure 1 here]

The strong connection between loan officer employment and housing cycles may not be surprising per se.[1] However, the pro-cyclical movement of loan officer employment is still noteworthy, as a rapid increase in new officers may raise questions about the performance of mortgages that originated during the boom. That is, at the peak, mortgage applications are more likely to be screened and processed by novices who just started their jobs in the wake of the housing boom. Given that loan officers have substantial discretion on loan approval decisions and their loan screenings are critical to future loan performances (Agier, 2012; Bushman et al., 2021; Tzioumis and Gee, 2013), it is essential to clarify whether the qualities of mortgages handled by less experienced officers are the same as those processed by the more experienced.

This paper thus investigates the impacts of loan officers' experience on mortgage performance and, ultimately, the housing market fluctuations. Despite the importance of the lending officer's role in mortgage origination, there has been little work that examines the impact of loan officer experience, mainly due to the lack of data. For instance, on the loan performance side, although the prevailing view is that the experience is negatively correlated with delinquency rates as loan officers gain expertise over time (Andersson, 2004; Beck et al., 2013), the causal relationship has never been formally tested. Also, some arguments suggest the work experience of officers may not enhance, or indeed exacerbate, loan performances: loan officers are typically under a probation period for the first 1–2 years, potentially making

[1] The close linkage between house prices and lending officer employment is understandable, considering the demand for loan officer positions rises during booms while the entry barrier to the profession has generally been not that high.

them more careful in screening lemon applications. Moreover, new loan officers are likely to be the ones who recently completed the pre-license education and qualification tests, and thereby they might be better at following the protocols of loan screening by the book.

This study attempts to fill in the void by utilizing novel individual loan officer-level data collected by the Nationwide Mortgage Licensing System (NMLS). I begin by examining the relationship between years of experience as a loan officer and mortgage delinquency probability by running a linear probability regression. Using the matched dataset of individual mortgage officer- and mortgage performance-level information for 2018–2021 period, I find that an additional year of experience as a lending officer decreases delinquency rates by 0.045 to 0.066 percentage points. The magnitude of the reduction in delinquency probability is substantial, especially considering that the average delinquency rate over the sample period is only 2.7%.

Furthermore, I conduct a set of additional analyses to check the robustness of the main results. First, I address a potential concern that only officers with better screening abilities may have survived longer, as this sample selection bias might (falsely) generate a negative correlation between work experience and delinquency rates. Thus, I re-estimate the baseline regression after including individual loan officer fixed effects to eliminate the impacts from the time-invariant loan officer level difference. Second, I verify whether my results are biased by other factors, such as the systematic difference between banks and nonbanks and the conservative lending practice of senior loan officers. Overall, my results are robust across all tests.

My previous empirical results suggest that inexperienced officers are more likely to originate mortgages that should not be approved. As a next step, I turn to an investigation of the aggregate impact of inexperienced loan officers on the housing market. Specifically, I hypothesize that a mass entry of inexperienced officers increases house prices by allowing initially unqualified households to be eligible for home purchases. In addition to a simple OLS, I make use of an instrument variable (IV) specification by employing variations in state-wide licensing costs as an instrument. The results indicate that counties in states with larger inflows of new loan officer licenses face faster home price growths. In particular, 1 percent greater state-wide new license growth raises a county's house price growth rate by 0.0022 to 0.0105 percentage points, depending on specifications. In sum, inexperienced officers not only affect individual loan performances but also influence home prices by originating greater amounts of mortgages than the optimal level.

Then, motivated by my empirical findings, I establish a partial equilibrium model of lending amount decisions of the representative bank. In the model, lending officers are hired by the bank, initially with an "unskilled" status. Every period, unskilled loan officers become "skilled" with probability, because they gain experience by working longer. Loan officers play a crucial role in the lending amount decision by calculating the expected future loss amount: while skilled officers form a correct expectation about the future, unskilled workers are overly optimistic and underestimate the loss. Namely, the more unskilled officers are hired by the bank, the more undercalculated the future loss of mortgage origination. As the bank wants to achieve the zero-profit condition, it originates more mortgages than optimal when the future loss is undervalued. The rise in mortgage origination amount, in turn, increases the employment of new, unskilled, loan officers in the next period, creating positive feedback loops.

I compare the simulated outcome of my model to the benchmark where lending officers always start their careers with a "skilled" status. My model with unskilled officers has a greater response to a temporary shock in house prices, displaying house price momentum. Naturally, it takes a longer time to return to the steady state price level. Moreover, due to the amplified housing cycle, the bank suffers a bigger loss in the downturn. The largest deficit in the model is estimated to be twice as much as that in the benchmark. Overall, the model presents how the positive interaction between house prices and new loan officer employment can magnify the housing market fluctuations, even without changes in market fundamentals.

In addition, using the model, I conduct two counterfactual policy experiments related to loan officer employment and training. First, I set a ceiling on the annual growth rate of loan officers to 2.5%, thus preventing the lending officer positions from being predominantly occupied by unskilled people. Second, I double the probability of unskilled officers becoming skilled, which could be accomplished by strengthening the internal training of employees. The results of the experiments suggest that policies that restrict the growth of loan officer employment and intensify training programs for newcomers can significantly reduce the negative consequences in the market.

My paper contributes to the literature that studies the role of individual loan officers in lending outcomes. For example, several studies examine the causal association between the specific characteristics of individual officers—e.g., gender (Beck et al., 2013), race (Frame et al., 2022), and ability (Agier, 2012)—and loan outcomes. Also, a strand of the literature focuses on the impact of incentive schemes offered to individual officers on loan origination and delinquency events (Agarwal and Wang, 2009; Agarwal and Ben-David, 2018; Behr et al., 2020; Berg, 2015; Hertzberg et al., 2010; Tzioumis and Gee, 2013). To the best of my knowledge, no study directly investigates the impact of the experience of loan officers, except Andersson

(2004). However, Andersson (2004) does not use real-world data and instead relies on the experimental setting, possibly limiting the applicability of the results. Another closely related work is the study of Gilbukh and Goldsmith-Pinkham (2021), which links the increase in inexperienced real estate agents to housing liquidity shock during the housing bust.

More broadly, my study is also related to the literature on credit cycle and house price momentum. Multiple studies show how the credit market and the real economy, including real estate prices, amplify each other by forming positive feedback loops (Bernanke and Gertler, 1990; Iacoviello, 2005; Kiyotaki and Moore, 1997). This paper may be also relevant to the literature that explains housing momentum through various mechanisms, such as search frictions (Head et al., 2014; Hedlund, 2016), extrapolative expectations (Case and Shiller, 1989), sentiment changes (Hott, 2011), and strategic complementarity (Guren, 2018). I add on to the literature by showing a new channel—loan officer employment channel—that could further propagate the housing cycle and generate price momentum.

Lastly, in the data matching process, my paper can also be connected to Buchak and Jørring (2021), Jiang et al. (2020), and Frame et al. (2022). Both Jiang et al. (2020) and Frame et al. (2022) combine the HMDA data and the NMLS loan officer-level data (NMLS data, hereafter), using the unique identification key provided in the private HMDA. Due to the lack of the access to the private HMDA, I connect the HMDA and the NMLS data using an alternative method: I first merge the NMLS data with the CoreLogic Mortage data, and then link the CoreLogic-NMLS data to the HMDA using loan level information contained in both the HMDA and the CoreLogic Mortgage data. Furthermore, as I also join the loan-level data to the loan performance information, I employ the methodology used by Buchak and Jørring (2021).

The remainder of this paper is organized as follows: Section 2 describes the data and summary statistics. Section 3 introduces the empirical methodology and presents the results. Section 4 illustrates a model that generates the positive feedback loops between house prices and loan officer employment. Section 5 concludes this study.

2 Data and Summary Statistics

2.1 Data

My analyses are based on residential mortgages that are sold to GSEs, Fannie Mae and Freddie Mac. To examine the impact of an individual officer's experience on mortgage performance, I need to combine individual officer-level information in the NMLS data with the GSE single-family loan performance data (GSE data, hereafter). However, the two datasets cannot be directly matched, because the GSE data does not contain the information on originating lending officers, which could be potentially used as a key matching variable.

Thus, to bridge the GSE and NMLS data, I utilize two additional datasets: the HMDA and the CoreLogic Mortgage data. Both datasets cover nearly the universe of loans originated in the US, with detailed loan- and borrower-level characteristics.[2] A brief description of the matching procedure is as follows. First, according to Buchak and Jørring (2021), the GSE and HMDA data can be matched using the information on the location (i.e., 3-digit ZIP code), the exact loan amount and interest rate, and the purchaser type (i.e., Fannie Mae or Freddie Mac). Second, loan-level observations of the CoreLogic Mortgage data contain the unique NMLS ID of the lending officer and thus can easily match with the NMLS data. Finally, I connect loans in the combined GSE-HMDA data and those in the CoreLogic-NMLS data on origination year and month, location (i.e., census tract), loan amount, and lending institution ID. After the matching, my final dataset contains 37,768 loan-level observations from 2018 to 2021.[3] More details on the data matching procedures are provided in Appendix A.

2.2 Variable Descriptions and Summary Statistics

The primary explanatory variable is the year of experience of individual loan officers. I define $Experience_{i,j}$ as individual j's total years of service as a loan officer when loan i is originated. I calculate this variable by subtracting the license/registration year of lending officer j from the origination year of loan i. I also define $Delinquent_{i,j}$ as a dummy variable that equals 1 if mortgage i originated by officer j has ever been delinquent for more than 60 days.[4] The borrower and loan-level control variables are the FICO score of the borrower, loan-to-value (LTV) ratio, debt-to-income (DTI) ratio, interest rate, mortgage amount, the county-level house price growth rates from 2018 to 2021, and the indicators of minority and female borrowers, respectively.

Panel A in Table 1 presents the summary statistics of the variables used in the loan-level regressions. My loan-level dataset contains 37,854 observations. The average delinquency rate for 30+ days, 60+ days, 90+ days, and 120+ days are 6.4%, 2.7%, 2.1%, and 1.7%,

[2] The central difference between the HMDA and CoreLogic Mortgage is that HMDA has information on the rejected loan applications while CoreLogic only contains data on approved mortgages.

[3] Since 2018, HMDA has provided additional loan-level information, such as interest rate, origination fees and discount points, loan-to-value (LTV) ratio, and debt-to-income (DTI) ratio. As interest rate is the key variable for the matching procedure, my analyses concentrate on the period after 2018.

[4] In further specifications, I also define $Delinquent_{i,j}$ as dummy variables that equal 1 if mortgage i originated by officer j has ever been delinquent for more than 30 days, 90 days, and 120 days, respectively.

respectively. The average year of experience of loan officers at origination is 6.58 years, and the standard deviation is 3.077. The mean FICO score is reported to be 755.72, with a standard deviation of 142.91. We also report each year's county-level house price growth rate from 2018 to 2021. The average price growth is 12.2% in 2021, the highest in the four years.

Moreover, in Panel B, we document the key statistics of the county-level variables used in the analyses in the following section. The sample period for the county-level analyses is from 2014 to 2021, and the data includes 20,777 observations. The county-level house price growth rate (i.e., $HP\ Growth_{c,t}$) is, on average, 5.9%. $\ln(New\ License_{state(c),t})$ and $\ln(License\ Fee_{state(c),t})$ are defined as the logarithms of new individual mortgage loan originator (MLO) license counts and MLO licensing fee in the state of county c in year t, respectively. The mean values of the variables are 5.324 and 5.081, and the standard deviations are 1.333 and 0.596.

[Table 1 here]

3 Empirical Methodology and Results

In this section, I describe my empirical model to investigate whether the experience of individual officers indeed matters in mortgage performances, and present the results. Then, I conduct a series of robustness tests to address the concerns related to my empirical specification and findings. Finally, I highlight the aggregate impact of inexperienced loan officers on the housing market. I show that the inflow of inexperienced officers further promotes house prices.

3.1 Effect of Loan Officer's Experience on Mortgage Performance

I first directly test whether delinquency rates decrease when loan officers become more experienced. In particular, I design the following linear probability regression:

$$Delinquent_{i,j} = \beta Experience_{i,j} + \gamma X_i + \eta_{county(i)} + \eta_{origin\_ym(i)} + \epsilon_{i,j}, \tag{1}$$

where i denotes a loan and j refers to an individual officer. The dependent variable is $Delinquent_{i,j}$, a dummy variable that equals 1 if mortgage i originated by officer j has ever been delinquent for more than 60 days. The main variable of interest is $Experience_{i,j}$, the total years of service of individual j as a loan officer when loan i is originated. X_i is a set of borrower and loan-level characteristics, including $FICO$, LTV, DTI, $Interest\ Rate$, *Loan Amount*, *Minority*, *Female*, 2018 *HP Growth*, 2018 *HP Growth*, 2020 *HP Growth*, and 2021 *HP Growth*. I also control for county- and origination year-month-specific variations by adding county and origination year-month fixed effects ($\eta_{county(i)}$ and $\eta_{origin\_ym(i)}$), respectively.[5]

Table 2 presents the results. Columns (1) and (2) show the results of the estimations that include county and origination year-month fixed effects. In column (1), the coefficient for $Experience_{i,j}$ is -0.0517, with the statistical significance at the 1% level, indicating that an additional year of experience is associated with 0.052 percentage point decrease in loan delinquency rates. In column (2), I further control for regional housing market conditions and the indicators of minority and female borrowers. The coefficient is -0.0446 and remains statistically significant. In columns (3) and (4), I add lending institution × origination year fixed effects to the baseline specification, and in columns (5) and (6), I substitute county × lending institution fixed effects for county fixed effects. I find that regardless of specification, increases in the loan officers' experiences significantly reduce loan delinquency rates. Moreover, the relationship is economically significant. An additional year of work experience decreases delinquency rates by 0.045 to 0.066 percentage points, and it is a sizable reduction given that the average delinquency rate is 2.7%.

[Table 2 here]

Figure 2 visualizes the results with a binned scatter plot and exhibits a strong negative relation between lending officer experience and loan delinquency rates. The linear fitted line implies that it takes a new lending officer 6.6 years to build up the skills to lower their delinquency rates to the average level.

[Figure 2 here]

Additionally, I test whether my empirical results vary when I define $Delinquent_{i,j}$ differently. Although more than 60 days of delinquency[6] is a standard measure in the mortgage literature (Athreya et al., 2018; Avery et al., 1996; Moulton, 2010), I adopt more than 30 days, 90 days, and 120 days of delinquency events in the calculation of $Delinquent_{i,j}$, and then repeat the analyses. Table 3 provides the results. I find that the experience of a lending officer has substantial impacts on both more than 90 days (columns (3) and (4)) and more than 120 days (columns (5) and (6)) of delinquencies. In contrast, lending officers' experiences

[5] I also test different sets of fixed effects in further specifications.

[6] When a loan is 60 days past due, the lender typically initiate acceleration procedures by sending a notification to the borrower.

do not have a significant impact on more than 30 days of mortgage delinquency (columns (1) and (2)). These results further emphasize the importance of loan officers with sufficient experience: a loan officer's experience plays a crucial role in preventing more severe credit events (i.e., 90+ and 120+ days delinquency) while having no meaningful impact on relatively mild credit events (i.e., 30+ days delinquency).

[Table 3 here]

3.2 Robustness Checks

In this section, I conduct a set of robustness tests to address potential concerns for my main findings.

3.2.1 Selection Bias Concern

There is a possibility that selection bias may lead to my main results. For example, if only loan officers with innate screening capabilities can survive longer in the business, then a significant negative correlation between the loan officer experience and delinquency rates would appear.

To alleviate this concern, I include individual loan officer fixed effects in the baseline equation (1).[7] The fixed effects sweep out the individual officer level unobserved time-invariant heterogeneity. Moreover, with the notion that individual officers' decisions may be influenced by the companies they work for, I redo my analyses after replacing individual loan officer fixed effects with individual loan officer × lending institution fixed effects.

In Table 4, I find no change in the sign and the significance of the coefficient of interest, even when I include additional fixed effects. The magnitude of the coefficient rather becomes stronger with those fixed effects. This confirms the robustness of my main results and suggests that the heterogenous survival rate among individual officers is not the driver of my estimates.

[Table 4 here]

3.2.2 Addressing Alternative Explanations

In addition to the selection bias concern, I rule out alternative explanations that might be consistent with my empirical findings. By confirming that my results are not coming from these

[7] The inclusion of individual loan officer fixed effects reduces my sample size by approximately half, potentially raising another empirical issue in sample construction. Plus, if I include individual officer fixed effects, then the variation of my main independent variable is restricted to only 3 years as my sample period is from 2018 to 2021. Despite all these concerns, individual officer fixed effects enables me to focus on a homogeneous sample of lending officers, accounting for the potential bias coming from the different survival rates of individual officers.

counter-explanations, I can shed light on the important role of the accumulated knowledge and skills of seasoned loan officers.

Banks vs. Nonbanks A certain type of lending institution may exhibit both higher delinquency rates and shorter work experiences, and my main result might be driven by these systematic differences between institution types. For example, several papers report that loans originated by the nonbank lending sector bear greater default risks (Gete and Reher, 2021; Hanson et al., 2015; Drechsler et al., 2022). Hence, if loan officers hired by nonbank lenders are in general younger than those employed by bank lenders, then a significant negative correlation between the loan officer experience and delinquency rates could falsely show up.

To account for this possibility, I separately estimate the baseline model of equation (1) using nonbank and bank subsamples. The results are documented in Table 5: columns (1) – (3) and columns (4) – (6) present the estimation results using nonbank and bank subsamples, respectively. The results of each subgroup are highly comparable to the baseline estimates in Table 1, indicating that the difference in institution type is unlikely to bias my main findings.

[Table 5 here]

Conservativeness of Senior Officers Another alternative explanation for the significant effect of loan officer experience on loan performances is that approval rates are different between senior and junior officers. For instance, if loan officers become conservative as their total years of work experience increase, then loans originated by more experienced officers would naturally show lower delinquency rates.

To verify that my estimates are not caused by the conservative lending practice of senior officers, I run a panel regression on approval rates using lending institution-county pairs. Specifically, I build a new panel dataset by calculating the average loan approval rate from the HMDA and the average total years of work experience of lending officers from the NMLS data, both at the lending institution-county-year level. Using the dataset, I estimate the following equation:

$$Approval\ Rate_{l,c,t} = \beta Avg\_Experience_{l,c,t} + \gamma X_{c,t} + \eta_l + \eta_c + \eta_t + \epsilon_{l,c,t}, \tag{2}$$

where l indicates to a lending institution, c denotes a county, and t refers to a year. Here, the dependent variable is $Approval\ Rate_{l,c,t}$, the average mortgage approval rate of lending institution l located in county c in year t. The main independent variable is $Avg\_Experience_{l,c,t}$, the average year of work experience of loan officers working at lending institution l located in county c in year t. $X_{c,t}$ is a vector of county-specific controls computed from the HMDA, including the log average income of mortgage applicants ($\ln(Avg\_Income)$), the average loan-to-income (LTI) ratio of applications (Avg_LTI), the share of female applicants ($Share\_Female$), and the share of minority applicants ($Share\_Minority$) in county c in year t.[8] Finally, η_l, η_c, and η_t stand for lending institution, county, and origination year fixed effects, respectively.[9] By running this regression, I examine whether the average year of experience is significantly associated with the average approval rate.

Columns (1) – (3) in Table 6 present the results of the approval rate regression. Column (1) shows the result using the entire sample of lending institution-county pairs. I find no evidence of the conservative lending behavior of senior officers: approval rates increase with the average year of experience of lending officers, indicating that veteran officers take more risks in processing loan applications. The result can be understood as signifying the senior's expert skills to cherry-pick better applications from the pool of similar risk profiles. I also consider the possibility that the senior's conservative lending practice may only occur in high-risk application pools. To verify this, I re-run the regression in equation (2) using the observations in counties whose median incomes are bottom 50 percent (i.e., low-income county) and top 50 percent (i.e., high-income county), respectively. Columns (2) and (3) provide the results of the estimations for high- and low-median income county samples. In both columns, the coefficients of $Avg\_Experience$ are significantly positive, echoing the result in column (1). Interestingly, the coefficient in column (3) (i.e., low-median income county sample) is bigger and statistically more significant than that in column (2) (i.e., high-median income county sample), meaning that the risk-taking behavior of senior officers is even more pronounced in the low-income counties, riskier application pools.

In addition, I check whether the average riskiness of loan applications is different according to the average work experience of loan officers. High-risk applicants may have an incentive to find and self-select a green loan officer so they could enhance the odds of approval. Columns (4) – (6) in Table 6 present the results of the regressions of various risk profiles on the average experience of officers. I observe no significant association between risk profiles and the average work year of lending officers. Overall, the results in Table 6 point that the conservative lending practice of senior officers is not a major driving force behind my findings.

[8] The underlying assumption for controlling for county-level characteristics is that all mortgages within a county are applied to lenders located in the same county.

[9] As a complementary specification, I use lending institution $\times$ county fixed effects instead of including lending institution and county fixed effects separately.

[Table 6 here]

3.3 Aggregate Effect of Inexperienced Loan Officers on House Prices

My empirical findings in the previous section highlight that less experienced officers are more likely to originate loans that would eventually be delinquent. This implies that those loans—that ended up with delinquency—may have not been approved if they were handled by more experienced personnel. It immediately follows an additional hypothesis that a mass inflow of inexperienced loan officers may escalate house prices as the imperfect screening of novices may make originally unqualified households eligible for home purchases. In this regard, I examine the aggregate effect of new loan officer entries on house prices by running county-level panel regression. Specifically, I model the following equation:

$$HP\ Growth_{c,t} = \beta \ln(New\ License_{state(c),t}) + \gamma X_{c,t} + \eta_t + \epsilon_{c,t}. \tag{3}$$

where $HP\ Growth_{c,t}$ is the growth rate of the Zillow Home Value Index (ZHVI) of county c during year t. $\ln(New\ License_{state(c),t})$ is the log of new individual MLO license counts issued in the state of county c in year t. $X_{c,t}$ is a vector of county-year specific controls, including population growth, the shares of black, non-white Hispanic, and white populations, and the log of median household income. η_t is year fixed effects. The sample period is from 2014 to 2021.[10]

Before presenting the results of my analyses, I first tabulate the number of new MLO license counts by state and year in Panel A in Table 7. There are a few points to note. First, during 2014–2021 period, the number of licenses issued every year has considerably grown. For example, in 2014 only 13,220 licenses were issued, whereas more than 40 thousand people obtained new MLO licenses in 2021. This uptrend had been persistent over the whole sample period, except for temporary drops in 2017 and 2018. Second, although the upturn in MLO issuance was a nationwide phenomenon, a huge variation in the growth of new licenses between states is observed. For example, in 2014, District of Columbia and the state of Michigan had similar numbers of new MLO licenses, 147 and 150, respectively. Then, in 2021, the number of new licenses in Michigan exceeded 800, while the number in District of Columbia was only one third of Michigan's (i.e., 262).

[10] Although the Secure and Fair Enforcement (SAFE) for Mortgage Lending Act requires any individual who takes a residential mortgage loan application must be licensed or registered as an MLO since 2009, the act allows existing loan originators to take time to acquire MLO licenses. I believe that all the new license issuances from 2014 (i.e., after five years since the SAFE act) can certainly be considered new entrants.

[Table 7 here]

The results of the estimation of equation (3) are shown in Table 8. In columns (1) and (2), I find that the coefficient of $\ln(New\ License_{state(c),t})$ is significantly positive in both regressions with and without county controls. The coefficients range from 0.0022 to 0.0043, suggesting that 1 percent greater state-wide new license growth raises a county's house price growth rate by 0.0022 to 0.0043 percentage points.

[Table 8 here]

However, simply regressing new NMLS license counts on house prices might be problematic, given that NMLS licensing growth is not unrelated to the local housing market condition. To mitigate this potential endogeneity concern, I exploit the variation in the costs of earning a new NMLS license. Following the Secure and Fair Enforcement (SAFE) for Mortgage Lending Act, each state has its own MLO licensing regulation. The applicants are typically required to take pre-license education courses, pass the qualification test (i.e., SAFE test), finish the criminal background check, and pay the license application and processing fee. Notably, there are substantial differences in the dollar amount of licensing fees across states as shown in Panel B in Table 7, while other requirements are extremely similar. For example, the application fee that MLO license applicants must pay is only \$30 in Colorado, while the costs are \$865 and \$645 in Hawaii and Massachusetts, respectively. Assuming that this variation affects house prices only by changing the number of new licenses, I can causally estimate the effect of new entries of inexperienced officers on the housing market prices.[11] I, therefore, use the following IV specifications:

$$\begin{aligned}\text{(First Stage)}\quad & \ln(New\ License_{state(c),t}) = \beta \ln(License\ Fee_{state(c),t}) + \gamma X_{c,t} + \eta_t + \epsilon_{c,t}, \\ \text{(IV)}\quad & \text{HP Growth}_{c,t} = \beta \ln(New\ \widehat{License}_{state(c),t}) + \gamma X_{c,t} + \eta_t + \epsilon_{c,t}, \end{aligned} \tag{4}$$

where $\ln(License\ Fee_{state(c),t})$ is the logarithm of MLO licensing fee of the state of county c. In the first stage regression, I expect the coefficient of $\ln(License\ Fee_{state(c),t})$ to be negative because higher licensing costs reduce new license applications, decreasing the number of new MLO licenses.

[11] There could be an endogeneity concern that the amount of licensing fee in each state might be determined by the state-wide house price level. However, even within a state, the house price levels greatly vary across counties or finer geographical divisions, making it less likely that the state-wide house price is the primary determinant of the state-level fee. Nevertheless, to rule out the potential of licensing fees being endogenous, I run the specification in equation (4) after excluding all states where house prices in the cheapest county exceed the national average house price. The results are qualitatively similar to my findings.

Columns (3) – (6) in Table 8 present the IV estimation results. Columns (3) and (4) show the first stage results. The results are consistent with the expectation, implying that a higher licensing fee discourages people from applying for new licenses: 1 percent increase in the fee is associated with 0.2094 to 0.2875 percent fewer new licenses. In columns (5) and (6), the estimates of the IV regression indicate that an increase in new licenses promotes housing prices by 0.0067 to 0.0105 percentage points. These magnitudes are even greater than those in the OLS specification in columns (1) and (2), and the results suggest again that the entry of inexperienced loan officers has an aggregate impact on house market prices.

4 Model

In this section, I establish a partial equilibrium model of the representative bank's lending amount decision to borrowers. Specifically, in the model, skilled and unskilled officers work for the bank, and these two types differ in their ability to calculate future losses. The mortgage amount, house prices, and entry of new (unskilled) officers are determined in the model, interacting with one another. The model builds upon the framework of Hott (2011). Hott (2011) presents a partial equilibrium model, greatly simplifying the general equilibrium models that describe the connection between credit, housing prices, and economic outcomes (Calza et al., 2007; Iacoviello, 2005; Kiyotaki and Moore, 1997).

There are broadly two advantages of utilizing the modeling framework: first, the model can demonstrate how the positive feedback effect between the house price and the (unskilled) loan officer employment further propagate the housing market fluctuations. That is, by modeling the interaction between the house price and the hiring of loan officers, I present that the housing boom can be created by a small temporary shock to the market, even without any changes in market fundamentals. Second, using the model, I can study the impacts of counterfactual policies that are related to loan officer employment and training (e.g., increasing the entry barrier to loan officer positions and strengthening the internal training of new employees). The results of my exercises suggest that such policies may protect the market, as well as banks, from devastating fallouts.

I begin with the benchmark model where there are only skilled loan officers. Then, I extend the model by allowing two types (i.e., skilled and unskilled) of loan officers.

4.1 Benchmark

4.1.1 Model Setup

(a) Housing

There is a fixed supply of S identical houses. I normalize S to one for simplicity. It is assumed that the housing unit is owned by the representative household, not banks. The period t house price is denoted by p_t.

(b) Household

There is a representative household in the economy. The household utility comes from consumption (c_t) and housing (h_t), with a well-defined utility function (i.e., $u(c_t, h_t)$) that satisfies the basic properties, such as monotonicity, concavity, and boundedness. I assume that to purchase a house ($h_t = 1$), a household must borrow one-period home purchase mortgage from the bank, at 100% LTV and a fixed interest rate, m ($m > 0$). In every period, the household also receives $i.i.d.$ income, y_t, uniformly distributed between 0 and $\bar{Y}$. The household can use its income for the mortgage repayment and consumption.

In addition, as in Hott (2011), I assume that household discount rate is greater than mortgage interest rate, m, meaning that the borrower is less patient than the lender. This condition implies that the household take the highest amount of mortgage to buy a house, and thus the borrowing constraint is always binding.[12] Therefore, I can abstract the explicit functional form of the utility function, and instead, I can focus on the household borrowing constraint for the remainder of the analyses.

Household Borrowing Constraint The value of housing stock owned by the household in period t equals p_t. Because the LTV is assumed to be 100% above, and the household can purchase a house only through mortgages, the mortgage amount is always the same as the value of housing stock occupied by the household, p_t. In addition, the mortgage payment that is due in period t equals $m \times p_{t-1}$, and the capital gain from housing from $t-1$ to t is $p_t - p_{t-1}$. Thus, the budget constraint of the representative household can be written as

[12] This condition is imposed in the models such as Calza et al. (2007), Iacoviello (2005), and Kiyotaki and Moore (1997).

follows:

$$\underbrace{y_t}_{\text{HH income}} + \underbrace{p_t - p_{t-1}}_{\text{capital gain}} \geq \underbrace{c_t}_{\text{consumption}} + \underbrace{mp_{t-1}}_{\text{mortgage repayment}}. \tag{5}$$

where c_t denotes the household consumption in period t. As c_t cannot be negative, the household defaults on its mortgage if the realized income y_t is less than $(1+m)p_{t-1} - p_t$.

Figure 3 graphically shows the household's expected net payment to the bank in $t+1$, according to its realized income. There are several noticeable points in the figure: first, as income is uniformly distributed between 0 and $\bar{Y}$, the probability that the household not being able to repay its mortgage (i.e., become delinquent) is $\frac{(1+m)p_t - E[p_{t+1}]}{\bar{Y}} \in [0,\ 1]$. Second, I assume that when the household becomes delinquent, it must sell its houses and use the proceeds and entire income to pay its mortgage duties. Hence, the household's net payment increases with its income realization in the insolvent income area (i.e., $\big[0,\ (1+m)p_t - E[p_{t+1}]\big]$), whereas the household's net payment is constant (i.e., $(1+m)p_t - E[p_{t+1}]$) in the solvent income area (i.e., $\big[(1+m)p_t - E[p_{t+1}],\ \bar{Y}\big]$).[13] Lastly, the bank's loss amount is maximized when the realized income is zero, and the loss monotonically decreases as the household income increases. Therefore, the expected loss for the next period (i.e., $E[\rho_{t+1}]$) can be calculated as the area of the shaded triangle: $E[\rho_{t+1}] = \frac{1}{2\bar{Y}}\big[(1+m)p_t - E[p_{t+1}]\big]^2$.

[Figure 3 here]

(c) Bank

The third element is the banking sector. I assume that there is a representative bank in the economy, and the bank supplies the household one-period home purchase mortgage at LTV 100%. Moreover, I assume that the market is perfectly competitive, and the bank is risk neutral. Due to the perfectly competitive environment, the bank takes the market prices. Specifically, it originates mortgages and finance itself at exogenously given rates, m and r, respectively ($m > r > 0$). As the bank is a price taker, the only decision that it makes is the mortgage origination amount in each period t, p_t.[14]

[13] The household will then use the remaining wealth (i.e., $y_{t+1} - ((1+m)p_t - E[p_{t+1}])$) in consumption, c_{t+1}.

[14] Another dimension of decision that the bank could make is whether to approve or reject the mortgage application. However, in the model, I assumed there is the representative household, implying that all households are ex ante homogeneous. Therefore, in the rest of the analyses, I focus on the bank's loan amount decision, assuming that the loan application will be approved.

Loan Officer Employment The bank hires loan officers to process new loan applications, as well as collect mortgages originated in the last period. I simplify the wage paid to loan officers to zero, and therefore the loan officer employment does not affect the profit of the bank. To define the law of motion of the loan officer employment, I instead assume that the bank adjusts the number of loan officers according to the loan origination amount. Assuming that each employee can handle up to the mortgage amount of τ, the number of loan officers in period $t+1$ (l_{t+1}) is expressed as:

$$l_{t+1} = \frac{p_t}{\tau}. \tag{6}$$

It follows that if mortgage amount increases (decreases) in period t, then $(p_t - p_{t-1}) \times \frac{1}{\tau}$ of new officers will be hired (fired) in the following period, $t+1$.

4.1.2 Equilibrium

Now, I derive the period t mortgage amount, and the house price, p_t.[15] Because the market is perfectly competitive, and also the bank is a price taker, the bank originates the mortgage amount (p_t) up to the level at which the bank attains zero profit. By originating mortgage amount p_t, the bank earns interest margin income of $p_t(m-r)$ in period $t+1$. At the same time, the bank's expected loss in $t+1$ due to household insolvency will be: $E(\rho_{t+1}) = \frac{1}{2\bar{Y}}[(1+m)p_t - E(p_{t+1})]^2$. Therefore, the expected profit of the bank in period $t+1$ (i.e., $E(\pi_{t+1})$) can be expressed as:

$$E(\pi_{t+1}) = p_t(m-r) - E(\rho_{t+1}). \tag{7}$$

The condition that ensures the bank's zero profit is thus:

$$\begin{aligned} E(\pi_{t+1}) &= 0 \\ \Rightarrow \; p_t(m-r) &= E(\rho_{t+1}) \\ &= \frac{1}{2\bar{Y}}[(1+m)p_t - E(p_{t+1})]^2. \end{aligned} \tag{8}$$

In the steady state where $p_t = E(p_{t+1}) = \bar{p}$, equation (8) can be rewritten as:

$$m - r = \frac{1}{2\bar{Y}} m^2 \bar{p}. \tag{9}$$

[15] In my model, the house price is always equal to the mortgage amount.

By rearranging the terms in equation (9), the amount of mortgage origination, and the house price, in the steady state is calculated as:

$$\bar{p} = \frac{2(m-r)\bar{Y}}{m^2} \tag{10}$$

Finally, the number of loan officers hired in the steady state equilibrium is: $\bar{l} = \frac{\bar{p}}{\tau} = \frac{2(m-r)\bar{Y}}{\tau m^2}$.

4.1.3 Parameterization and Simulation

In this section, I illustrate a numerical example of the benchmark model by setting parameter values and imposing a one-time housing market shock. Specifically, I set the parameter values of the model as follows:

- $m = 0.04$;
- $r = 0.02$;
- $\tau = 100$; and
- $\bar{Y} = 4$.

The rationales for choosing theses parameter values are provided in Appendix B. To obtain the steady state values, I plug the above parameter values into equation (9). By doing so, the steady state house price—and the mortgage amount—is calculated as $\bar{p} = 100$. Also, dividing $\bar{p} = 100$ by τ, I obtain the steady state employment of loan officers, $\bar{l} = 1$.

One-Time Housing Market Shock Assuming that the market is in the steady state in period 1, I impose a temporary housing market shock in period 2: a 3 percent increase in the house price ($p_2 = 103$). Figure 4 summarizes the dynamics of the house prices and the bank profits following the shock.

[Figure 4 here]

First, as the house price rise is unexpected in period 2, fewer delinquency events happen. Thus, the bank achieves a positive excess profit in period 2 (π_2):

$$\pi_2 = p_1\left(m - r - \frac{[(1+m)p_1 - p_2]^2}{2\bar{Y}p_1}\right) = 1.88. \tag{11}$$

Because the price increase was only a one-time shock, and because the fundamental values (i.e., m, r, and $\bar{Y}$) have not changed, the house price in period 3 returns to the steady state level (i.e., $p_3 = 100$).[16] Due to the decrease in the house price (103 to 100), the bank's profit in period 3 (i.e., π_3) turns negative:

$$\pi_3 = p_2\left(m - r - \frac{[(1+m)p_2 - p_3]^2}{2\bar{Y}p_2}\right) = -4.27. \tag{12}$$

Since period 4, the house price remains at the steady state level, 100, and the bank obtains zero profit every period. The employment of loan officers is also adjusted according to the house price changes (i.e., $l_1 = l_2 = 1$, $l_3 = 1.03$, $l_t = 1\ \forall t \geq 4$). To sum up, a temporary housing market shock only has a one-shot impact on the market, without any longer-term aftereffect.

4.2 Model with Unskilled Loan Officers

4.2.1 Skilled and Unskilled Loan Officers

In the benchmark model in the previous section, I assume that the bank is always accurate in predicting the future loss (i.e., $E(\rho_{t+1}) = \frac{1}{2\bar{Y}}[(1+m)p_t - E(p_{t+1})]^2$). However, given my empirical findings, I need to incorporate the fact that less experienced officers are more likely to approve mortgage applications that would eventually end up being delinquent.

To model the aforementioned feature, I introduce a new element into the model. I now assume that there are two types of lending officers in the bank: skilled and unskilled officers. Skilled officers are proficient in their loan screening and processing jobs, so they do not make any errors, as in the benchmark environment. On the other hand, there are unskilled officers, who are not yet perfect in their jobs, making forecast errors in the future outcomes of mortgages. Whenever new loan officers are employed, they start their careers with an "unskilled" status. Then, in each period t, the share δ of unskilled officers become "skilled," as they gain sufficient experience by working longer. In this regard, I can express the law of motion of the number of unskilled lending officers (u_t) by:

$$u_{t+1} = \underbrace{l_{t+1} - l_t}_{\text{change in new officers in } t+1} + \underbrace{(1-\delta)u_t}_{\text{remaining unskilled officers from } t}, \text{ where } u_t \geq 0\ \forall t. \tag{13}$$

[16] The calculation of p_3 is from the zero-profit equation, $m - r = \frac{m^2 p_3}{2\bar{Y}}$, which assumes that the bank expects the house price in period 4, $E(p_4)$, to be equal to p_3. This condition is reasonable considering that there is no expected change in any fundamental values..

Also, I assume that the bias of the bank in predicting the future loss amount is increasing with the share of the unskilled officers (i.e., $\frac{u_t}{l_t} \in [0, 1]$). Specifically, I model the "biased" expected loss under the presence of unskilled workers ($E(\rho'_{t+1})$) as follows:

$$E(\rho'_{t+1}) = \left(1 - \theta\frac{u_t}{l_t}\right) \times E(\rho_{t+1}) \tag{14}$$
$$= \frac{\left(1 - \theta\frac{u_t}{l_t}\right)}{2\bar{Y}}[(1+m)p_t - E(p_{t+1})]^2.$$

where $E(\rho_{t+1})$ is the correct expected loss amount when there are only skilled officers, and θ is a parameter that shows the extent to which unskilled officers created a bias in the future loss calculation.

There are two notable things regarding equation (14). First, if the share of unskilled officers is zero (i.e., $\frac{u_t}{l_t} = 0$), then $E(\rho'_{t+1})$ is exactly the same as $E(\rho_{t+1})$, thus generating the identical steady state outcome. Secondly, the bias under unskilled officers can be viewed as the extent to which the borrower's income is over-estimated. After the rearrangement of terms, $E(\rho'_{t+1})$ is equal to $\frac{1}{2\frac{\bar{Y}}{1-\theta\frac{u_t}{l_t}}}[(1+m)p_t - E(p_{t+1})]^2$, which is the expected loss under the income distribution $U[0,\ \frac{\bar{Y}}{1-\theta\frac{u_t}{l_t}}]$. Because $\frac{\bar{Y}}{1-\theta\frac{u_t}{l_t}}$ is greater than $\bar{Y}$, equation (14) can be interpreted as an upward bias in the income distribution due to the presence of unskilled officers. As income is closely related to the borrower's creditworthiness (Albanesi et al., 2017; Beer et al., 2018), this bias can be understood as an overestimation of the credibility of the borrower. Thus, my empirical findings in Section 3.1 is now incorporated in the model.

As in the benchmark case, the bank equalizes the (biased) expected loss (i.e., $E(\rho'_{t+1})$) with the interest rate margin (i.e., $p_t(m-r)$) to attain zero profit. With some rearrangements, I can obtain the price equation in the presence of unskilled loan officers as follows:[17]

$$p_t(m - r) = \frac{\left(1 - \theta\frac{u_t}{l_t}\right)}{2\bar{Y}}(mp_t)^2 \tag{15}$$
$$\Rightarrow p_t = \frac{2(m-r)\bar{Y}}{m^2\left(1 - \theta\frac{u_t}{l_t}\right)}.$$

4.2.2 Parameterization and Simulation

I turn into describing the result of the numerical example by setting the additional parameter values as: $\delta = 0.2$ and $\theta = 1.5$.[18] Again, the market is assumed to be in the steady state

[17] As in the previous section, I continue to assume that the bank expects $E(p_{t+1})$ to be equal to p_t.

[18] Appendix B explains the rationales for choosing these values.

with only skilled officers in period 1 ($p_1 = 100$, $l_1 = 1$, and $u_1 = 0$), and I impose the same temporary shock, a 3 percent increase in the house price in period 2 (i.e., $p_2 = 103$). This unexpected shock generates a positive excess profit to the bank in period 2 (i.e., π_2), as in the benchmark.

$$\pi_2 = p_1 \times \frac{m - r - [(1+m)p_1 - p_2]^2}{2\bar{Y}p_1} = 1.88. \tag{16}$$

Due to the increase in the mortgage amount in period 2, the bank needs to hire new lending officers in period 3, who are all unskilled. The new employment in period 3 is $(103 - 100) \times \frac{1}{100} = 0.03$, and the share of unskilled officers is therefore: $\frac{u_3}{l_3} = \frac{0.03}{1.03}$. As described in equation (15), the presence of unskilled officers creates a bias in the expected loss, which in turn further raises the house price in period 3 (p_3):

$$p_3 = 2 \times \frac{(0.04 - 0.02) \times 4}{0.04^2 \times \left(1 - 1.5 \times \frac{0.03}{1.03}\right)} = 104.57 \ (> p_2 = 103). \tag{17}$$

That is, because of the increase in unskilled officers in response to the house price increase, a one-time increase in house price has a longer-term impact.

Figure 5 displays the dynamics under the model with unskilled officers after a temporary shock in period 2. For the comparison, I also draw the benchmark results presented in Section 4.1.3. The house price rises up to 108.65 in period 6, due to the price momentum provoked by changes in unskilled officers. This is greatly different from the benchmark case, in which the price immediately returns to the steady state value in period 3. Then, the house price starts to decrease in period 7, after the bulk of unskilled workers become skilled, and eventually comes back to the initial steady state level in period 9. Furthermore, the house price drop is accelerated once it decrease, because the bank also adjusts its labor forces by firing unskilled officers.

[Figure 5 here]

Moreover, this amplified housing cycle has implications for the profit of the bank. The right panel of Figure 5 suggests that the larger housing cycle put the bank through a greater loss during the downturn.[19] Specifically, the bank's largest deficit is −8.31 in period 9, almost twice as much as the loss in the benchmark model (−4.28 in period 3). Even when all other

[19]Figure 5 suggests that the bank profits and losses are not symmetrical, demonstrating a sharp collapse after a gradual boom. It reproduces the past housing crisis that happened in 2008 (Mian et al., 2013; Mian and Sufi, 2009, 2014).

periods are being considered, the bank still suffers a bigger loss. The discounted sum of profits and losses using the bank's financing cost (2%) as the discount rate is calculated as -7.54, while it is -2.23 in the benchmark case.

4.3 Policy Experiments

In this subsection, I use my model to study two counterfactual policies related to loan officer employment and training. The results with those policies are compared with the outcomes presented in Section 4.2.2.

Entry Barrier to the Loan Officer Positions I first study the effect of raising the entry barrier to loan officer positions by restricting the maximum annual growth of loan officer employment to 2.5%. In practice, this ceiling may be achieved by adjusting the pass rate of MLO licensing tests, requiring more time for pre-licensure education, or increasing the amount of surety bond. Indeed, the policies listed above are the prerequisites for prospective MLO licensees documented in the SAFE Mortgage Lending Act.[20]

Figure 6 plots the outcomes with the counterfactual employment growth ceiling. The result is striking: the housing price evolves much less when the pro-cyclical loan officer employment growth is limited. Although it still shows momentum, the price comes to the steady state level in period 6, much faster than in the model without 2.5% entry ceiling.. In addition, the bank faces less severe loss, with the discounted total sum of profits and losses of -3.22.

[Figure 6 here]

Intensive Internal Training for Unskilled Officers Another way to mitigate the problem is to reduce the time it takes for unskilled loan officers to become skilled, for example, by offering more intensive internal training programs to new employees. In the previous section, I have assigned the conversion rate (δ) value of 0.2, meaning that on average, it takes 5 years for the unskilled to be skilled. I now double the value of δ to 0.4 and see how different the results are.

Figure 7 plots the results after changing the value of δ to 0.4. The figure indicates similar results to the policy exercise with entry restriction: the house price increase is moderate, and the discounted sum of profits and losses is -4.11, less devastating compared to the outcomes in the model with δ being 0.2. Overall, the results of the experiments suggest that policies that

[20] Fuster et al. (2021) show that the employment growth of mortgage loan officers during the 2020 housing boom fell short due to these time-consuming licensing hurdles.

limit the entry of new loan officers and strengthen training programs for beginning officers can significantly reduce the negative consequences in the market.

[Figure 7 here]

5 Conclusion

This study investigates the role of loan officers' experience in mortgage performance and the housing market fluctuations. Despite the growing emphasis on the role of mortgage lending officers, the actual impact of their experience has never been formally examined, due to the lack of data on individual lending officers. I overcome the limit by utilizing novel loan officer-level data collected by the NMLS.

Using the matched dataset of the NMLS, CoreLogic Mortgage, HMDA, and GSE data for 2018–2021 period, I find that loan officers' experience is significantly associated with the delinquency rates of loans originated by them. The results are economically significant, and remain intact to a series of robustness checks, including addressing the selection bias concern and alternative explanations.

Furthermore, with the empirical results in the first part, I investigate the aggregate impact of a mass entry of inexperienced lending officers on the housing market. As new loan officers are more likely to qualify the must-be-rejected households, their growing influx may promote house prices in the area. Both the OLS and IV specifications strongly indicate that counties in states with larger inflows of new loan officers experience higher home price growth rates.

Finally, motivated by the empirical findings, I build a partial equilibrium model of the lending amount decision of the representative bank. In the model, loan officer employment and house prices formulate positive feedback loops, so an initial positive shock to the housing market creates a larger housing cycle. Due to the propagated cycle, the bank suffers more seriously from losses during the downturn. Counterfactual policy experiments suggest that the negative consequences can be prevented by policies such as restricting the growth of loan officer employment and intensifying training programs for newcomers.

Taken together, this paper sheds light on the importance of the accumulated experience of lending officers, and suggests that policies that could minimize the negative impact of de novo lending officers can be useful tools in preventing adverse consequences in the market.

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Figure 1 House Price and Loan Officer Employment

This figure shows the percentage increases in the house price index and loan officer employment. The house price index data is obtained from the Federal Housing Finance Agency (FHFA) and the loan officer employment data is from the Bureau of Labor Statistics (BLS).

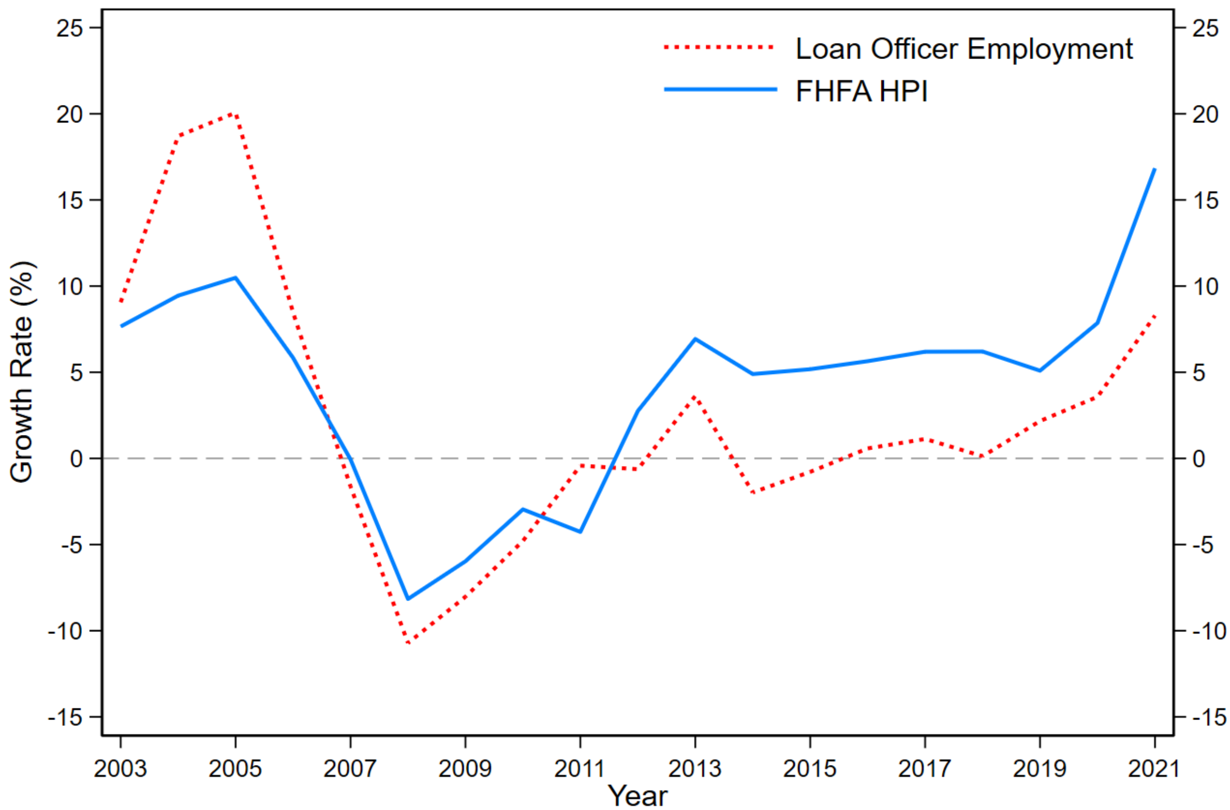

Figure 2 Years of Loan Officer Experience and Mortgage Delinquency Rates

This figure plots the residualized Delinquency and in each Experience decile. The full set of control variables (FICO, LTV, DTI, Interst Rate, Loan Amount, Minority, Female, 2018 HP Growth, 2019 HP Growth, 2020 HP Growth, and 2021 HP Growth) are used to residualize both Delinquency and Experience.

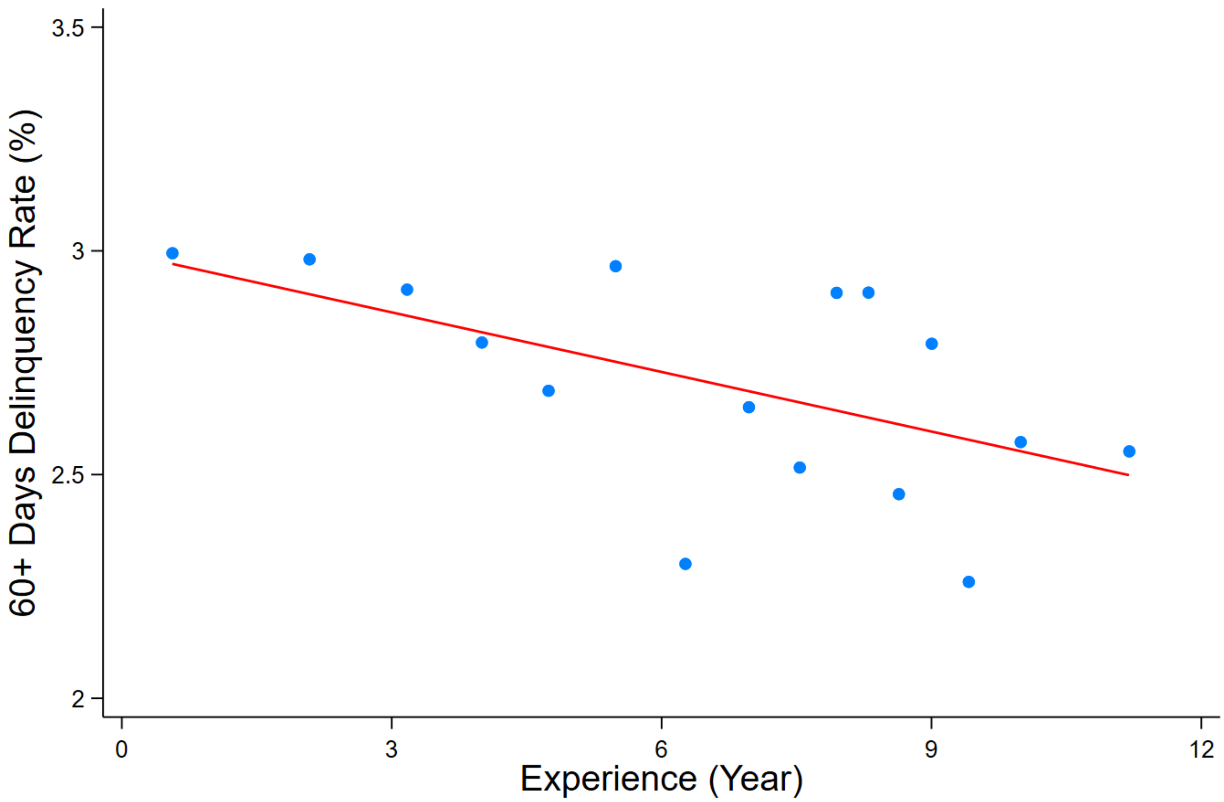

Figure 3 Household Income and Net Mortgage Payment to the Bank

This figure illustrates the net mortgage payment of the household to the bank, according to the realized income in period $t + 1$. The gray area indicates the expected loss amount of the bank due to the household insolvency.

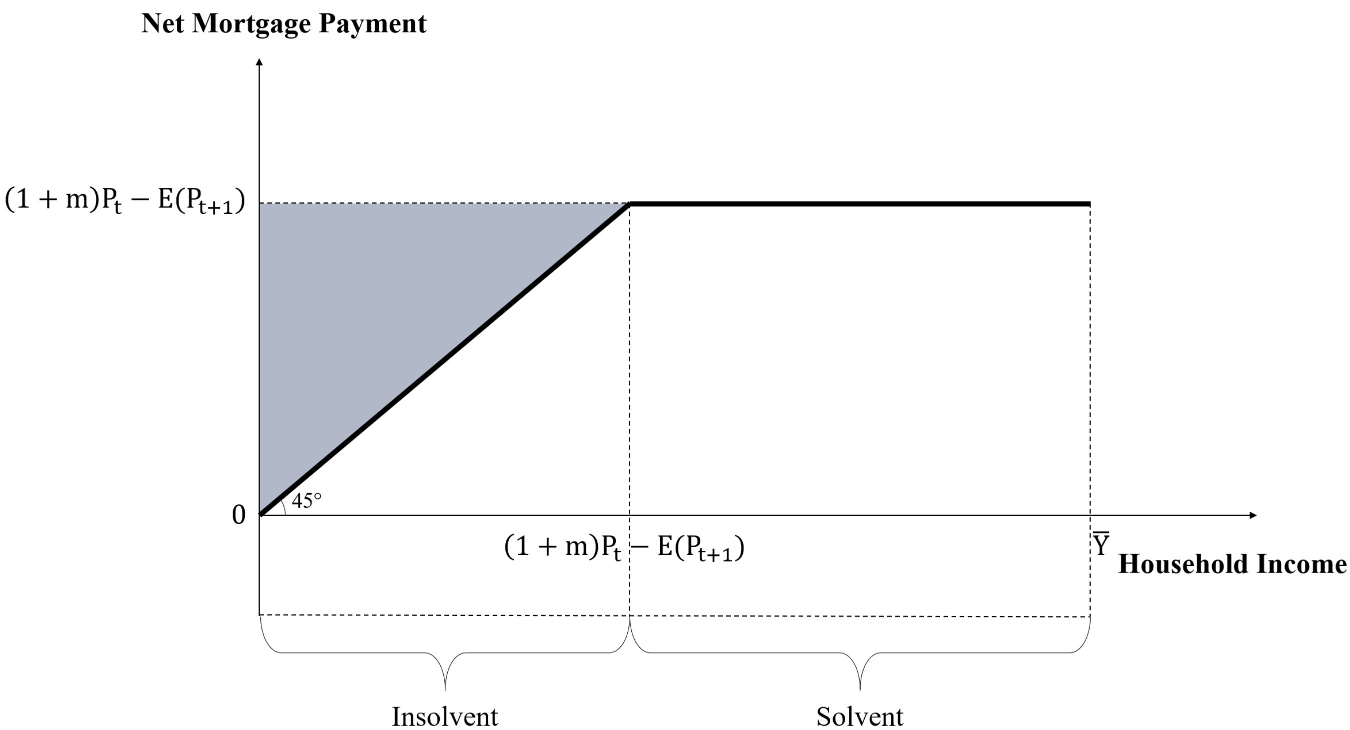

Figure 4   Simulation Results: Benchmark

This figure plots the simulated house prices and profits of the bank for the benchmark. As a price shock, a 3% house price increase in period 2 is imposed.

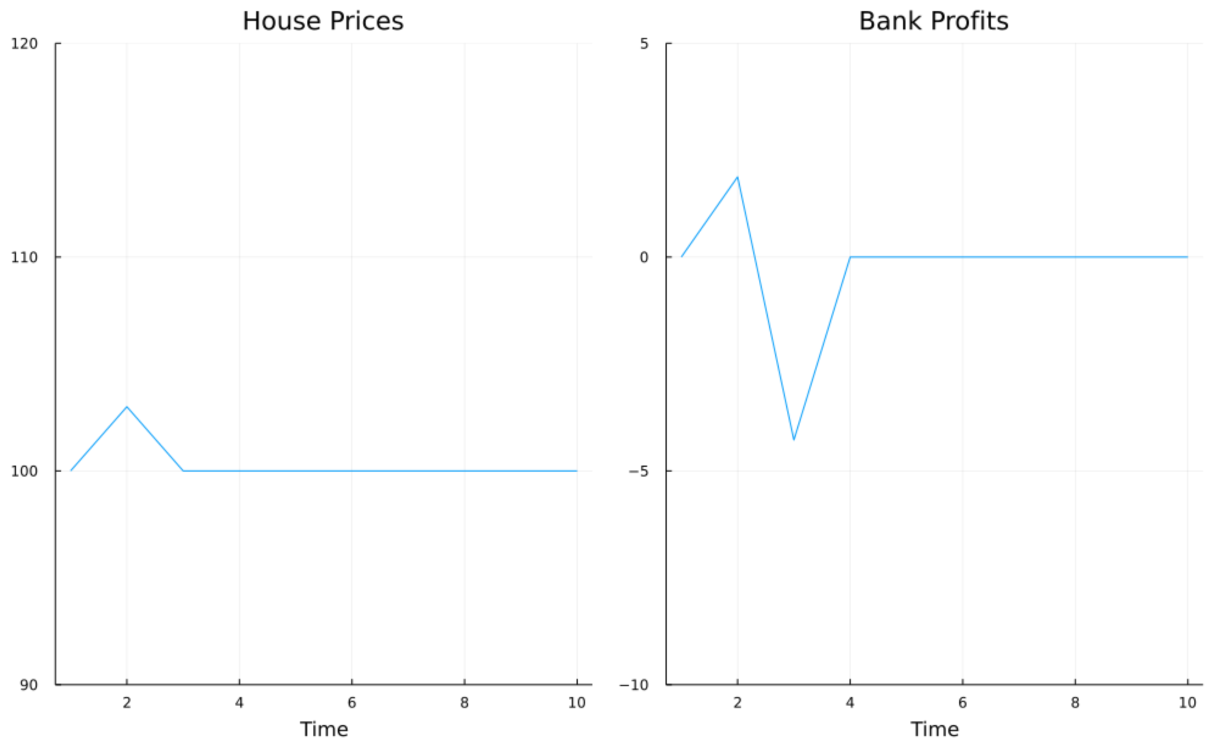

Figure 5 Simulation Results: Model with Unskilled Lending Officers

This figure plots the simulated house prices and profits of the bank for my main model. As a price shock, a 3% house price increase in period 2 is imposed. For the comparison, I also plot the benchmark results.

Figure 6 Policy Experiment: With and Without 2.5% Entry Ceiling

This figure plots the simulated house prices and profits of the bank for the model with and without the 2.5% restriction in percentage increase in new loan officers. As a price shock, a 3% house price increase in period 2 is imposed.

Figure 7   Policy Experiment: With and Without Intensive Internal Training Programs

This figure plots the simulated house prices and profits of the bank for the model with and without intensive training programs for new employees. When there is a training program for novices, then δ is set to 0.4, twice as large as the initial value, 0.2. As a price shock, a 3% house price increase in period 2 is imposed.

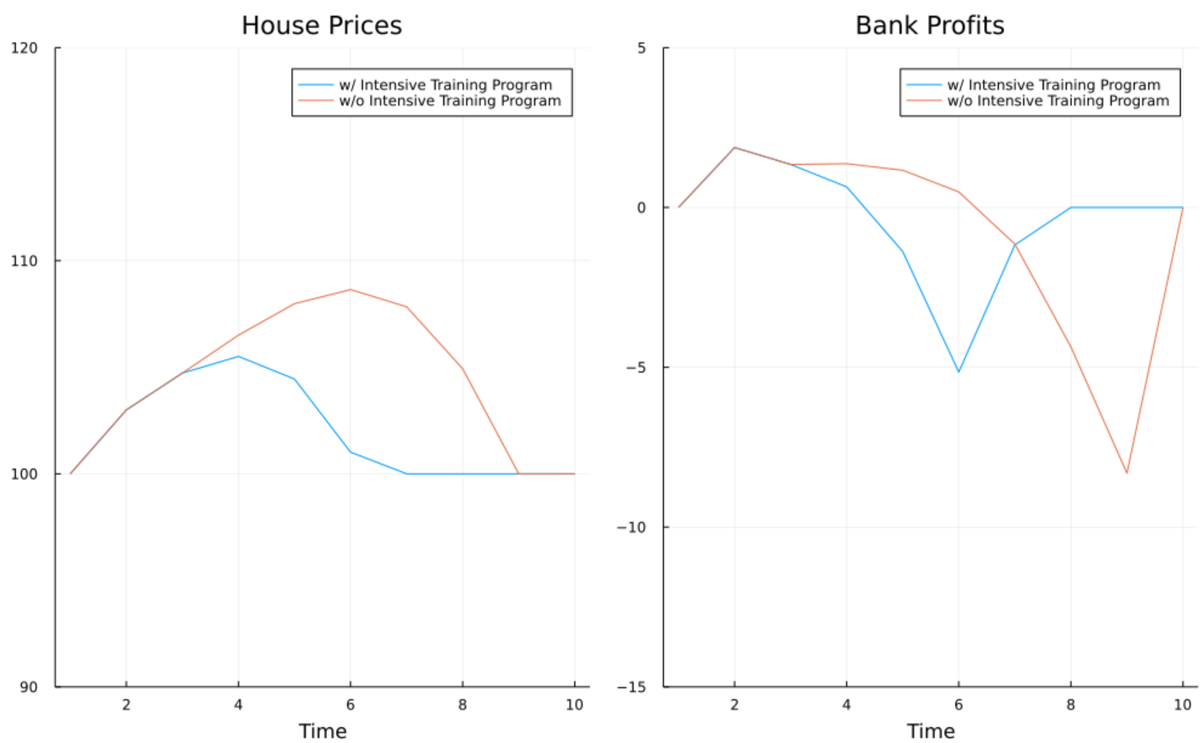

Table 1 Summary Statistics

The table reports the summary statistics of the variables for my analyses. Panel A reports loan-level variables. $\text{Delinquent}_{i,j}$ is a dummy variable that equals 1 if mortgage i originated by officer j has ever been delinquent for more than 30 days, 60 days, 90 days and 120 days, respectively. $\text{Experience}_{i,j}$ is the total years of service of individual j as a loan officer when loan i is originated. FICO_i is the FICO score of the applicant of loan i. LTV_i, DTI_i, Interest Rate_i, and Loan Amount_i are the loan-to-value ratio, debt-to-service ratio, interest rate, and loan amount of loan i at origination, respectively. Minority_i and Female_i indicate whether the applicant of loan i is from racial and ethnic minority groups and female, respectively. 2018 HP Growth_i, 2019 HP Growth_i, 2020 HP Growth_i, and 2021 HP Growth_i are the annual growth rate of house prices in county where loan i is originated in 2018, 2019, 2020, and 2021. Panel B reports county-level variables. HP $\text{Growth}_{c,t}$ is the annual growth rate of house prices in county c in year t. ln(New $\text{License}_{state(c),t}$) and ln(License $\text{Fee}_{state(c),t}$) are the logarithms of new individual mortgage loan originator (MLO) license counts and mortgage loan originator licensing fee in the state of county c in year t, respectively. Population $\text{Growth}_{c,t}$ is the population growth of county c in year t. % $\text{Black}_{c,t}$, % Non-White $\text{Hispanic}_{c,t}$, and % $\text{White}_{c,t}$ stand for the shares of black, non-white Hispanic, and white population, respectively. ln(Median $\text{Income}_{c,t}$) is the log of median household income in county c in year t. Median $\text{Age}_{c,t}$ is the median age of residents in county c in year t.

	Mean	S.D.	P1	P25	P50	P75	P99	Obs.
Panel A. Loan-level Variables								
Delinquent:								
30+ Days Delinquent	0.064	0.244	0.000	0.000	0.000	0.000	1.000	37,854
60+ Days Delinquent	0.027	0.162	0.000	0.000	0.000	0.000	1.000	37,854
90+ Days Delinquent	0.021	0.142	0.000	0.000	0.000	0.000	1.000	37,854
120+ Days Delinquent	0.017	0.128	0.000	0.000	0.000	0.000	1.000	37,854
Experience	6.580	3.077	0.000	4.000	7.000	9.000	13.000	37,854
FICO	755.717	142.912	630.000	722.000	767.000	793.000	819.000	37,821
LTV (%)	69.672	19.448	17.000	59.000	75.000	82.000	97.000	37,854
DTI (%)	35.873	39.966	10.000	27.000	36.000	43.000	50.000	37,854
Interest Rate (%)	3.791	0.966	1.990	3.000	3.625	4.500	5.875	37,854
Loan Amount ($000,000s)	2.442	1.537	0.350	1.250	2.150	3.350	7.050	37,854
Minority	0.280	0.449	0.000	0.000	0.000	1.000	1.000	37,854
Female	0.311	0.463	0.000	0.000	0.000	1.000	1.000	37,854
2018 HP Growth	0.060	0.026	0.003	0.043	0.060	0.075	0.139	37,833
2019 HP Growth	0.046	0.019	0.003	0.035	0.044	0.058	0.099	37,833
2020 HP Growth	0.036	0.018	-0.014	0.028	0.037	0.046	0.075	37,833
2021 HP Growth	0.122	0.036	0.031	0.099	0.121	0.145	0.203	37,833
Panel B. County-level Variables								
HP Growth	0.059	0.049	-0.032	0.031	0.049	0.074	0.230	20,777
ln(New License)	5.324	1.333	1.792	4.682	5.247	6.068	8.537	25,524
ln(License Fee)	5.081	0.596	3.434	4.615	5.198	5.442	6.447	25,524
Population Growth	0.001	0.019	-0.031	-0.005	-0.001	0.006	0.039	25,758
% Black	0.090	0.144	0.000	0.006	0.023	0.102	0.643	22,688
% Non-White Hispanic	0.034	0.067	0.000	0.006	0.014	0.034	0.383	22,688
% White	0.829	0.170	0.235	0.758	0.895	0.952	0.988	22,688
ln(Median Income)	10.747	0.295	9.729	10.593	10.756	10.914	11.453	22,688
Median Age	40.954	5.286	27.700	37.800	40.900	44.000	54.300	22,688

Table 2 Year of Loan Officer Experience and Mortgage Delinquency

This table shows the results of the linear probability regression of the effect of loan officer experience on mortgage delinquency. The dependent variable is 60+ Days Delinquent$_{i,j}$, a dummy variable that equals 1 if mortgage i originated by officer j has ever been delinquent for more than 60 days. The main independent variable of interest is Experience$_{i,j}$, the total years of service of individual j as a loan officer when loan i is originated. In all specifications, I include control variables such as FICO, LTV, DTI, Interst Rate, and Loan Amount and in even columns, I further include Minority, Female, 2018 HP Growth, 2019 HP Growth, 2020 HP Growth, and 2021 HP Growth. Columns (1) and (2) include county and origination year-month fixed effects. Columns (3) and (4) add lender × origination year fixed effects to the first two columns. Columns (5) and (6) replace county fixed effects in columns (3) and (4) with lender × county fixed effects. The t-statistics are reported in parentheses and all standard errors are clustered at the county level. ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	60+ Days Delinquent					
	(1)	(2)	(3)	(4)	(5)	(6)
Experience	-0.0517***	-0.0446**	-0.0556**	-0.0510**	-0.0663**	-0.0603*
	(-2.57)	(-2.23)	(-2.44)	(-2.20)	(-2.08)	(-1.89)
FICO	-0.0040***	-0.0040***	-0.0042***	-0.0042***	-0.0038***	-0.0038***
	(-2.69)	(-2.70)	(-2.61)	(-2.62)	(-2.71)	(-2.70)
LTV	0.0340***	0.0325***	0.0356***	0.0337***	0.0328***	0.0302***
	(6.08)	(5.91)	(5.64)	(5.43)	(4.54)	(4.16)
DTI	0.0162***	0.0161***	0.0164***	0.0164***	0.0142*	0.0143*
	(3.89)	(3.89)	(3.83)	(3.84)	(1.72)	(1.73)
Interest Rate	1.6313***	1.6404***	1.6793***	1.6786***	1.5720***	1.5663***
	(8.85)	(8.98)	(8.24)	(8.37)	(5.07)	(5.13)
Loan Amount	0.2252***	0.2344***	0.1789**	0.1895**	0.1405	0.1551
	(3.16)	(3.17)	(2.39)	(2.40)	(1.41)	(1.46)
Minority		0.8384***		0.8837***		1.0131***
		(3.93)		(3.42)		(2.75)
Female		-0.1022		-0.1287		-0.2026
		(-0.55)		(-0.60)		(-0.63)
2018 HP Growth		0.0478		0.0901		0.0700
		(0.51)		(0.91)		(0.42)
2019 HP Growth		-0.1290		-0.0230		-0.0795
		(-0.85)		(-0.14)		(-0.42)
2020 HP Growth		0.2524		0.2216		0.2250
		(1.43)		(1.12)		(0.96)
2021 HP Growth		0.0068		-0.0063		0.0639
		(0.06)		(-0.05)		(0.40)
County FE	✓	✓	✓	✓		
Origin Year-Month FE	✓	✓	✓	✓	✓	✓
Lender × Origin Year FE			✓	✓	✓	✓
Lender × County FE					✓	✓
R^2	0.061	0.062	0.192	0.193	0.357	0.358
Obs.	37,768	37,747	33,160	33,140	22,880	22,864

Table 3 Alternative Delinquency Measures

This table shows the results of the linear probability regression of the effect of loan officer experience on mortgage delinquency, using alternative measures of delinquency. The dependent variables are 30+ Days Delinquent$_{i,j}$, 90+ Days Delinquent$_{i,j}$, and 120+ Days Delinquent$_{i,j}$, a dummy variable that equals 1 if mortgage i originated by officer j has ever been delinquent for more than 30 days, 90 days, and 120 days, respectively. The main independent variable of interest is Experience$_{i,j}$, the total years of service of individual j as a loan officer when loan i is originated. In all specifications, I include control variables such as FICO, LTV, DTI, Interst Rate, and Loan Amount and in even columns, I further include Minority, Female, 2018 HP Growth, 2019 HP Growth, 2020 HP Growth, and 2021 HP Growth. All columns include county and origination year-month fixed effects. The t-statistics are reported in parentheses and all standard errors are clustered at the county level. ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	30+ Days Delinquent		90+ Days Delinquent		120+ Days Delinquent	
	(1)	(2)	(3)	(4)	(5)	(6)
Experience	-0.0447	-0.0335	-0.0401**	-0.0342**	-0.0341**	-0.0285*
	(-0.92)	(-0.72)	(-2.43)	(-2.04)	(-2.37)	(-1.91)
FICO	-0.0076***	-0.0077***	-0.0032***	-0.0032***	-0.0026***	-0.0026***
	(-2.71)	(-2.73)	(-2.74)	(-2.76)	(-2.73)	(-2.75)
LTV	0.0400***	0.0388***	0.0319***	0.0310***	0.0271***	0.0262***
	(4.84)	(4.51)	(6.62)	(6.47)	(6.56)	(6.40)
DTI	0.0194***	0.0194***	0.0131***	0.0131***	0.0083*	0.0083*
	(3.84)	(3.87)	(2.72)	(2.72)	(1.94)	(1.93)
Interest Rate	3.2405***	3.2482***	1.2632***	1.2716***	1.1404***	1.1485***
	(11.87)	(12.25)	(7.65)	(7.74)	(7.72)	(7.89)
Loan Amount	0.2260**	0.2175**	0.1965***	0.1957***	0.1550***	0.1590***
	(2.18)	(1.99)	(3.34)	(3.25)	(2.98)	(3.01)
Minority		1.4056***		0.6945***		0.6383***
		(4.82)		(4.28)		(3.98)
Female		-0.3054		-0.1416		-0.0717
		(-1.19)		(-1.02)		(-0.54)
2018 HP Growth		0.1148		0.0299		0.0087
		(0.75)		(0.29)		(0.09)
2019 HP Growth		-0.2019		0.0888		0.1419
		(-0.86)		(0.66)		(1.19)
2020 HP Growth		0.0311		0.1219		-0.0032
		(0.10)		(0.90)		(-0.02)
2021 HP Growth		0.0308		-0.0886		-0.0043
		(0.18)		(-0.93)		(-0.05)
County FE	✓	✓	✓	✓	✓	✓
Origin Year-Month FE	✓	✓	✓	✓	✓	✓
R^2	0.070	0.070	0.055	0.056	0.051	0.051
Obs.	37,768	37,747	37,768	37,747	37,768	37,747

Table 4 Addressing Seletion Bias Concerns

This table shows the results of the linear probability regression of the effect of loan officer experience on mortgage delinquency, including additional fixed effects that control for the time-invariant heterogeneity between individual officers. The dependent variable is 60+ Days Delinquent$_{i,j}$, a dummy variable that equals 1 if mortgage i originated by officer j has ever been delinquent for more than 60 days. The main independent variable of interest is Experience$_{i,j}$, the total years of service of individual j as a loan officer when loan i is originated. In all specifications, I include control variables such as FICO, LTV, DTI, Interest Rate, and Loan Amount and in even columns, I further include Minority, Female, 2018 HP Growth, 2019 HP Growth, 2020 HP Growth, and 2021 HP Growth. All columns include county and origination year-month fixed effects. Also, columns (1) and (2) additionally include individual officer fixed effects and columns (3) and (4) include lender × individual officer fixed effects. The t-statistics are reported in parentheses and all standard errors are clustered at the county level. ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	60+ Days Delinquent			
	(1)	(2)	(3)	(4)
Experience	-0.8843***	-0.8965***	-0.8484***	-0.8572***
	(-3.35)	(-3.35)	(-3.84)	(-3.85)
FICO	-0.0118	-0.0117	-0.0113	-0.0112
	(-1.12)	(-1.12)	(-1.40)	(-1.40)
LTV	0.0343***	0.0326***	0.0345***	0.0331***
	(3.21)	(3.09)	(4.05)	(3.93)
DTI	0.0178**	0.0183**	0.0191***	0.0196***
	(2.48)	(2.53)	(3.05)	(3.12)
Interest Rate	1.4646***	1.4607***	1.3840***	1.3749***
	(4.03)	(4.01)	(4.86)	(4.81)
Loan Amount	0.1508	0.1648	0.1676	0.1758*
	(1.20)	(1.30)	(1.65)	(1.71)
Additional Controls		✓		✓
County FE	✓	✓	✓	✓
Origin Year-Month FE	✓	✓	✓	✓
Individual Officer FE	✓	✓		
Lender × Individual Officer FE			✓	✓
R^2	0.434	0.435	0.439	0.440
Obs.	20,960	20,942	19,964	19,946

Table 5 Addressing Counter Explanations: Nonbank and Bank Subsample Analyses

This table shows the results of the linear probability regression of the effect of loan officer experience on mortgage delinquency, separately using nonbank and bank subsamples. The dependent variable is 60+ Days Delinquent$_{i,j}$, 90+ Days Delinquent$_{i,j}$, and 120+ Days Delinquent$_{i,j}$, a dummy variable that equals 1 if mortgage i originated by officer j has ever been delinquent for more than 60 days, 90 days, and 120 days, respectively. The main independent variable of interest is Experience$_{i,j}$, the total years of service of individual j as a loan officer when loan i is originated. In all specifications, I include control variables such as FICO, LTV, DTI, Interst Rate, Loan Amount, Minority, Female, 2018 HP Growth, 2019 HP Growth, 2020 HP Growth, and 2021 HP Growth. Columns (1) — (3) use the nonbank subsample and columns (4) — (6) use the bank subsample. All columns include county and origination year-month fixed effects. The t-statistics are reported in parentheses and all standard errors are clustered at the county level. ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	Nonbanks			Banks		
	60+ Days Delinquent	90+ Days Delinquent	120+ Days Delinquent	60+ Days Delinquent	90+ Days Delinquent	120+ Days Delinquent
	(1)	(2)	(3)	(4)	(5)	(6)
Experience	-0.0582**	-0.0350	-0.0250	-0.0376	-0.0534*	-0.0471*
	(-2.01)	(-1.64)	(-1.22)	(-1.33)	(-1.79)	(-1.83)
FICO	-0.0070**	-0.0052**	-0.0046**	-0.0031**	-0.0027**	-0.0021**
	(-2.08)	(-2.15)	(-2.23)	(-2.26)	(-2.32)	(-2.27)
LTV	0.0264***	0.0265***	0.0224***	0.0371***	0.0344***	0.0290***
	(3.87)	(4.46)	(3.91)	(4.70)	(4.92)	(5.04)
DTI	0.0158***	0.0096***	0.0058	0.0159**	0.0155**	0.0095
	(5.16)	(2.71)	(1.38)	(2.09)	(2.02)	(1.43)
Interest Rate	1.3178***	1.0102***	0.9033***	1.9683***	1.5768***	1.4120***
	(5.96)	(5.48)	(5.12)	(6.88)	(5.94)	(6.29)
Loan Amount	0.2911***	0.2150***	0.1788**	0.2299**	0.2123**	0.1646**
	(3.36)	(2.85)	(2.48)	(2.07)	(2.37)	(2.23)
Additional Controls	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
Origin Year-Month FE	✓	✓	✓	✓	✓	✓
R^2	0.080	0.071	0.066	0.086	0.079	0.075
Obs.	19,166	19,166	19,166	18,464	18,464	18,464

Table 6 Addressing Counter Explanations: Conservative Lending Practice of Senior Officers

This table reports the panel regression results of the effect of the average year of experience of loan officers on the average approval rate. I use the lending institution-county-year level observations from 2018 to 2021. In Columns (1) – (3), the dependent variable is Approval Rate$_{l,c,t}$, the average approval rate of loans applied to lending institution l in county c in year t. The main independent variable of interest is Avg_Experience$_{l,c,t}$, the average year of work experience of loan officers working at lending intuition l in county c in year t. In Columns (3) – (4), I use Avg_Experience$_{l,c,t}$ as the dependent variable. All columns include control variables such as ln(Avg_Income), Avg_LTI, Share_Female, and Share_Minority. I include lending institution, county and year fixed effects in all specifications. The t-statistics are reported in parentheses and all standard errors are clustered at the county level. ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	Approval Rate			Avg_Experience		
	All Counties	High Income Counties	Low Income Counties	All Counties	High Income Counties	Low Income Counties
	(1)	(2)	(3)	(4)	(5)	(6)
Avg_Experience	0.0008***	0.0006*	0.0011**			
	(2.69)	(1.74)	(2.19)			
Avg_ln(Income)	0.0227	-0.0092	0.0536	-0.4689	-0.0870	-0.7291
	(1.36)	(-0.38)	(1.61)	(-1.53)	(-0.17)	(-1.39)
Avg_LTI	-0.0003	-0.0005	0.0002	-0.0019	0.0003	-0.0051
	(-0.59)	(-0.86)	(0.35)	(-0.39)	(0.06)	(-0.57)
Share_Female	-0.0397	0.0534	-0.0843	1.0535	2.9119*	0.7874
	(-0.86)	(0.49)	(-1.46)	(1.42)	(1.68)	(0.83)
Share_Minority	-0.0674	-0.1535*	0.0079	-0.7311	0.6363	-1.4430
	(-1.44)	(-1.83)	(0.12)	(-0.77)	(0.35)	(-1.05)
Lag HP Growth	0.0199	-0.0326	0.0265	-0.2284	-0.3513	-0.9694
	(0.81)	(-0.82)	(0.79)	(-0.47)	(-0.43)	(-1.17)
Year FE	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
Lender FE	✓	✓	✓	✓	✓	✓
R^2	0.406	0.399	0.434	0.287	0.278	0.328
Obs.	29,758	15,015	14,533	30,141	15,209	14,718

Table 7 NMLS Individual Mortgage Loan Originator Licenses and Licensing Fees

This table reports the number of NMLS MLO license issuance and the amount of licensing fees in each state. Panel A presents the number of NMLS individual MLO license issuance by state and year. Panel B shows the dollar amount of individual MLO license application and processing fee by state in 2020.

Panel A. NMLS Mortgage Loan Originator License Issuance by State and Year

State	2014	2015	2016	2017	2018	2019	2020	2021
AL	1,538	2,392	3,078	2,777	2,546	2,208	3,543	4,350
AK	103	176	288	422	347	304	646	515
AZ	1,223	1,962	2,739	2,706	2,200	2,439	5,312	5,858
AR	200	202	295	578	444	412	584	938
CA	3,058	3,458	4,781	5,097	3,926	3,681	6,496	8,170
CO	386	477	770	860	690	562	967	1,469
CT	280	312	436	592	354	304	371	643
DE	132	132	200	219	177	88	244	276
DC	147	167	222	203	180	130	234	262
FL	1,523	1,818	2,183	3,039	2,895	2,492	3,600	5,243
GA	272	296	503	625	507	438	576	723
HI	60	67	102	97	84	82	111	164
ID	105	104	116	202	149	143	160	225
IL	272	298	529	602	425	366	477	823
IN	204	251	309	358	264	201	272	370
IA	63	49	106	135	88	80	157	183
KS	51	60	90	126	143	76	116	232
KY	112	130	231	179	120	102	115	159
LA	112	143	163	193	198	137	179	275
ME	46	36	60	83	70	63	87	126
MD	127	146	215	242	223	157	204	405
MA	73	102	168	206	182	166	216	282
MI	150	214	305	316	270	211	364	809
MN	134	131	193	243	187	138	174	294
MS	58	44	73	66	54	47	55	50
MO	74	81	116	173	117	94	111	266
MT	17	15	45	29	39	30	40	56
NE	15	26	20	32	27	16	31	53
NV	164	156	205	237	216	202	217	362
NH	10	13	16	21	14	15	16	32
NJ	242	276	354	439	390	318	376	535
NM	36	55	76	89	70	63	72	118
NY	117	154	224	281	221	203	176	253
NC	182	209	366	389	399	283	431	748
ND	4	5	9	11	10	5	7	13
OH	69	109	138	204	204	181	235	448
OK	71	80	132	149	132	89	108	259
OR	190	225	264	333	297	221	262	406
PA	132	128	179	214	173	137	167	509
RI	1	6	14	16	20	19	17	29
SC	86	85	127	160	171	73	148	263
SD	7	9	16	30	17	10	18	18
TN	104	126	169	226	173	124	162	366
TX	716	746	980	1,218	1,259	1,007	1,208	2,584
UT	123	178	253	273	224	196	310	483
VT	6	8	7	13	8	4	6	12
VA	104	140	188	189	186	137	254	393
WA	273	235	331	403	313	347	412	685
WV	4	7	18	12	7	9	11	15
WI	40	60	60	121	98	61	84	148
WY	4	9	15	21	14	7	8	19
Total	13,220	16,308	22,477	25,449	21,522	18,878	30,147	41,917

Panel B. NMLS Mortgage Loan Originator Licensing Fee by State

State	Licensing Fee (2020)	State	Licensing Fee (2020)
AK	630	MT	430
AL	105	NC	155
AR	80	ND	105
AZ	622.13	NE	180
CA	330	NH	130
CO	30	NJ	180
CT	330	NM	430
DC	330	NV	105
DE	530	NY	409
FL	300.25	OH	230
GA	230	OK	490
HI	865	OR	110
IA	80	PA	230
ID	230	RI	630
IL	230	SC	80
IN	130	SD	180
KS	130	TN	230
KY	80	TX	100
LA	230	UT	230
MA	645	VA	180
MD	256	VT	130
ME	50	WA	155
MI	80	WI	280
MN	120	WV	230
MO	80	WY	150
MS	231		
Average	249.28		

Table 8 Mortgage Loan Originator License and House Price Growths

This table shows the results of the regression of the effect of entry of new loan officers on county-level house prices. Columns (1) and (2) report the OLS regression results. The dependent variable is HP Growth$_{c,t}$, the growth rate of the Zillow Home Value Index (ZHVI) of county c in year t. The main independent variable is ln(New License$_{state(c),t}$) is the log of new individual MLO license counts issued in the state of county c in year t. Columns (3) – (6) present the IV regression results using ln(License Fee$_{state(c),t}$), the log of MLO licensing fee in the state of county c in year t, as an instrument. The dependent and main independent variables are identical to the OLS regression in columns (1) and (2). In columns (3) and (4), the first-stage regression results are documented. In all specifications, I include control variables such as Population Growth, % Black, % Non-White Hispanic, % White, ln(Median Income), and Median Age. All columns include year fixed effects. The t-statistics are reported in parentheses and all standard errors are clustered at the county level. ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	OLS		IV			
	HP Growth		ln(New License)		HP Growth	
	(1)	(2)	(3)	(4)	(5)	(6)
ln(New License)	0.0043***	0.0022**			0.0105***	0.0067***
	(5.06)	(2.64)			(3.97)	(3.87)
ln(License Fee)			-0.1493***	-0.2255***		
			(-10.28)	(-14.90)		
Population Growth		0.9401***		18.6109***		0.4388***
		(5.44)		(20.24)		(10.69)
% Black		-0.0334		1.0199***		-0.0262***
		(-1.55)		(6.00)		(-5.17)
% Non-White Hispanic		-0.0059		9.1565***		0.0241
		(-0.21)		(31.31)		(1.32)
% White		-0.0282		-0.6843***		0.0042
		(-1.51)		(-4.19)		(1.06)
ln(Median Income)		-0.0223***		-0.3136***		-0.0068***
		(-5.01)		(-7.83)		(-5.68)
Median Age		0.0001		0.0212***		0.0000
		(0.23)		(11.40)		(0.33)
Year FE	✓	✓	✓	✓	✓	✓
First-Stage F-Statistics			115.759	199.821		
R^2	0.186	0.254				
Obs.	18,036	18,035	20,769	18,028	20,769	18,028