Decentralized Banking in Mortgage Market: Evidence from Branch Manager's Past Experience*

(Preliminary and please do not circulate)

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Abstract

Do banks delegate their lending decisions to local branches? We examine this question in the mortgage market. Using a novel dataset connecting bank branch managers' decisions to their career histories, we find that managers' past experiences with mortgage approval and pricing significantly influence their subsequent lending standards even after they switch employments across firms and locations. Such effects are stronger for non-conforming loans as well as for loans to riskier borrowers, as these loans can entail larger losses and require more scrutiny from managers. We also find more prominent effects at branches that are farther away from bank headquarters. Fixing the manager-branch pair, we observe that mortgage rates exhibit amplified responses to policy shocks originating from monetary policies and bank stress tests when the shocks conform to managers' priors. Managers with contrary experiences exhibit muted responses to those shocks. Our results suggest that bank branch managers have autonomy in shaping local mortgage lending decisions.

JEL Codes: G21, G34, J60, J62

Keywords: Bank branch managers, mortgage, delegation, personal experience, monetary policy

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1. Introduction

The U.S. banking industry has undergone significant geographical expansion over the past few decades (Stiroh 2010; Goetz et al. 2016). Taking the mortgage market as an example, the typical bank lender receives loan applications from four states as of 2019, with the top ten lenders each originating loans in 47 states. As banks operate with increasing geographical scope, their decision chains need to adapt and accommodate the growing complexity of the organization. In particular, they face the choice of whether to delegate part of the lending authority to local branches.

According to canonical theories, a key benefit of delegation is that it incentivizes the efficient collection and use of soft information (Stiglitz and Weiss 1981; Rajan 1992; Aghion and Tirole 1997; Stein 2002). Despite the prevalence of digitization and securitization in credit markets, soft information continues to be critical for lenders to process and evaluate applications, especially for riskier segments of the market. At the same time, decentralized decision-making could create coordination challenges within the institution, impeding the implementation of bank-level policies such as lending standards and regulatory compliance. Thus, whether bank lending decisions are delegated locally remains an empirical question.

We study this question using the U.S. mortgage markets as a setting, for two reasons. First, borrowers in this market are highly local while lenders are geographically diverse, providing a need for delegation. Second, the geographical reach of mortgage lending decisions is a relevant question and an ongoing debate for policy design.[1]

Research on bank delegation faces the challenge that banks' internal decision processes are typically unobservable. To overcome this challenge, we examine the role of individual bank branch managers in influencing their branches' lending standards. These individuals have the highest authority in bank branches and carry out a wide range of

[1]For example, regulators state that "the market for mortgage lending has become national in scope" (Amel et al. 2018), justifying the implementation of nation-wide regulations. See also Federal Reserve's announcement: `https://www.federalreserve.gov/newsevents/pressreleases/orders20080605a.htm`. Yet, contemporaneous academic research suggests that competition exists at the local level (Fuster et al. 2013; Buchak and Jørring 2021), which may incentivize banks to delegate decision rights.

responsibilities.[2] We test whether these managers' idiosyncratic, personal experiences related to lending standards can shape their current lending decisions. Personal experiences have been shown to generate profound impacts on individual expectations, risk preferences, and ultimately their decision-making, even for sophisticated finance professionals (Carvalho et al. 2022; Malmendier et al. 2017; Koudijs and Voth 2016; Dittmar and Duchin 2016; Malmendier and Nagel 2011). Based on evidence from the literature, we expect past experiences to also shape managers' perceptions about the appropriate lending standards. If managers can set branch-level lending standards based on these perceptions, we should observe a link between their past experiences and current lending outcomes. For example, having experienced high interest rates in a previous job, a manager may consider the interest rates charged at the current branch to be "too low," and adjust the rates upwards if he has the power to do so.

To test this idea, we compile a unique dataset on branch managers that contains their detailed career records, from which we can track a manager's employment history at different banks, locations, and time. We identify a bank branch as the combination of a bank and a county. We then match manager career information with mortgage databases, including HMDA and CoreLogic, to extract the characteristics of loans extended at managers' previous and current bank branches. Our sample covers 10,263 managers working in 1,563 unique banks across 1,254 locations over the period of 1990–2017. Using this data, we find that bank managers' past experiences with both denial and interest rates significantly affect the corresponding outcomes at the current branch. Managers with different interest rate experiences also respond differently to monetary policy shocks and bank stress test failures.

We compute *Experience Gap* for each manager-branch pair as the difference between the manager's past experiences regarding denial (interest) rates and the pre-existing denial (interest) rates at his current branch. A high experience gap suggests that managers' experienced stricter lending standards during their past jobs compared to the current

[2]Bank branch managers oversee the daily operations of a branch, including supervising accounts, dealing with customer relations and disputes, hiring, firing, and disciplining employees, enforcing lending policies, etc. They also may directly engage in loan approvals or denials.

branch. We find a significant, positive relation between managers' experience gaps regarding denial (interest) rates and changes in denial (interest) rates at the new branch. Our estimates suggest that a one-standard-deviation increase in managers' experience gap for denial rates is associated with a 3-percentage-point increase in denial rate over the three years after the manager joins the bank, representing 29% of the standard deviation of denial rate changes. A one-standard-deviation increase in the experience gap over interest rates is associated with about a 4.3 basis points increase in interest rates over the same horizon, an 8% change relative to the standard deviation of interest rate variations.

Our baseline approach fixes a branch and tracks the changes in its lending policies over time. It also controls for past denial rates and interest rates at the county level. In stricter specifications, we further impose bank-by-year fixed effects to purge out any changes in bank-level conditions and compare how lending outcomes change differently across branches of the same bank according to their managers' past experiences. Our results remain robust to these controls. We conduct several additional analyses to strengthen our inference. First, we adopt an event study approach and show that the approval and interest rates at bank branches exhibit no significant changes prior to the arrival of a new manager. Importantly, they increase (decrease) significantly following the arrival of a manager with positive (negative) experience gap. This helps alleviate the concern that managers may match to branches based on pre-existing trends in lending standards. Next, we address the possibility that experiences accumulated earlier in one's career may matter differently compared to later ones. We show that our results remain robust when we measure experience gap using only recent experiences, and when we set a range of depreciation rates for earlier career experiences. Finally, our results remain unchanged when we focus on managers' prior experiences during job spans when they were *not* in management positions. This suggests that our results are not entirely driven by managers imposing their preferences in both previous and current branches. Taken together, our evidence is consistent with managers having the discretion to influence mortgage approval as well as pricing.

We substantiate the mechanisms underlying our findings by examining whether the manager experience effects become more pronounced in cases where managers are likely to have greater discretion. We start by comparing the effects of manager experiences in riskier market segments, such as jumbo loans, loans to low-income borrowers, and loans to low-credit-score borrowers, relative to other loans. For these loans, banks not only have more incentives to collect soft information to screen borrowers, but their lending decisions are also less constrained by uniform underwriting rules. We thus expect branch managers to have more discretion. Consistent with this conjecture, we find a stronger manager experience effect for riskier loan and borrower types. Additionally, we examine the role of market discipline and expect managers to have less power to influence lending standards when such standards are more constrained by prevailing market rates. Consistent with this conjecture, we find our effects to be significantly stronger in counties with more lenders and in counties with a more competitive mortgage market (indicated by lower Herfindahl index of mortgage origination volume across banks). Such heterogeneity supports the view that bank mortgage lending decisions are delegated to the local level. This allows the past idiosyncratic experiences of branch managers to be reflected in their current lending standards.

One remaining concern is that our central finding may be driven by branch-manager matching according to certain characteristics that also correlate with lending standards (such as personality, work style, bank culture, etc.). To overcome this concern, we design two analyses examining how managers respond to unexpected shocks after they have joined a branch. These shocks include monetary policy shocks and the passage and failure of bank stress tests. In these analyses, we fix the manager-branch pair and track the changes in branch lending policies around the shocks. We also compare across branches whose managers have conforming and non-conforming prior experiences to these shocks.

In the first analysis, we trace the responses of mortgage rates to monetary policy shocks. Unexpected monetary policy shocks serve as a good setting for identification because they are difficult to predict precisely. Thus banks are unlikely to base their hiring decisions on the realized policy shock. More importantly, changes in monetary policy is a first-order determinant of mortgage rates, and the passthrough of the policy has been shown to have important consequences for household and firm investments, as well as local economic growth (Campbell 2013; Drechsler et al. 2017; Garriga et al. 2017; Scharfstein and Sunderam 2016). Our findings could shed light on how lenders' personal experiences amplify or mitigate monetary policy transmission.

We look at how managers with different experiences adjust mortgage rates differently to monetary policy shocks, which we classify into either tightening or loosening. Tightening (loosening) shocks refer to positive (negative) surprises in the federal funds futures rate. We expect mortgage rates to have a stronger response when the policy shocks confirm the managers' "priors." Consistent with this conjecture, we find that mortgage rates increase substantially following a tightening policy shock when managers have positive experience gaps regarding interest rates, and decrease significantly after a loosening shock when managers have negative experience gaps. In contrast, when managers' past experiences conflict with the direction of the monetary policy shocks, there is little or small changes in mortgage rates. Overall, these findings suggest that managers' personal experiences represent a key source of heterogeneity in explaining the passthrough of monetary policies across banks and locations.

Our second experiment investigates the differential response in mortgage rates across branches when a bank fails stress tests. Following prior studies (e.g., Acharya et al. 2018; Cortés et al. 2020), we exploit the heterogeneity of timing and results of stress tests across large lenders. We first confirm the results in prior studies that banks who failed stress tests increase their mortgage rates. More importantly, branches whose managers have high interest rate experiences raise rates substantially more than other branches. Branches with low-rate-experience managers, in contrast, do not seem to respond to stress test failures. These results suggest that managers' idiosyncratic experiences shape the implementation of bank-level policies across branches.

When implementing these analyses, we impose several rigorous empirical specifications to address remaining concerns. For example, we include manager fixed effects to alleviate the concern related to dynamic manager-branch matching. This set of controls fixes the individual and tracks how the same manager responds differently to different policy changes over time. Another concern is that managers who started their previous jobs a long time ago may have a higher interest rate experience if interest rates have been trending down in the past. We show that our results remains unchanged when we demean interest rate experiences during each year in their past jobs. This approach removes aggregate time trends and captures the heterogeneity across managers' experiences accumulated at the same time in the past.

Taken together, our findings suggest that decentralized decision-making inside banks influences the passthrough of macroeconomic and bank-level policies. These results are relevant for assessing the effectiveness of policies as well as their distributional effects.

In closing, we investigate whether managers' experiences capture the characteristics, especially credit risk, of their loan applicants. We directly examine the link between manager experiences and applicant attributes, including income, demographics, and credit score. We do not find these characteristics to be associated with managers' experiences, either regarding interest rates or denial rates. In addition, we document that loans extended by high- and low-experience managers exhibit similar performance. This evidence suggests that the effects of manager experiences on interest rates and denial rates should not be driven by the matching of high-rate experience managers with high-risk borrowers.

This study contributes to several strands of literature. First, it is related to the growing literature on localized decision-making inside banks. A long-standing literature provides theoretical foundation for the benefits of delegated decision making inside banking organizations, including Aghion and Tirole (1997), Stein (2002), among others. Using small business loans data from other countries, Mian (2006) and Canales and Nanda (2012) find evidence consistent with decentralized decisions generating benefits for lenders. Relatedly, Mian and Sufi (2009), Cole et al. (2015), and Liberti and Petersen (2019) show that organization form and incentive design affect the type of information being collected and used by lenders. Berger et al. (2005) show that small banks have advantages in collecting and utilizing soft information in the small business loans market.

While evidence exists that other types of banking decisions can be influenced by lower level branches and employees, less is known regarding whether mortgage lending decisions are indeed delegated to local branches.[3] As the mortgage market becomes increasingly regulated and competitive, it remains an empirical question as to whether decisions in this market are centralized or at least partially delegated. We bridge this gap in the literature and provide micro-level evidence on this front. Specifically, we show that personal experiences of branch managers matter in setting lending standards and mortgage rates.

In addition, we add to the important literature on the determinants of mortgage lending standards. The extant literature largely focuses on the effects of macroeconomic policies, market-wide factors, borrower and bank fundamentals on mortgage origination and pricing (see, e.g., Loutskina and Strahan 2009, Mian and Sufi 2018, Justiniano et al. 2022 among others). Recent studies suggest that minority bank owners and loan officers influence the allocation of credit towards minority borrowers (Frame et al. 2021; Jiang et al. 2021). We differ from these studies by looking at the role of bank branch managers in influencing mortgage lending in a local market. Instead of focusing on manager fixed effects, we examine how managers' past experiences (which vary over time) shape local lending standards. Importantly, we show that manager experiences shape the transmission of monetary policies and the implementation of bank-level policies. In this regard, we contribute to the literature on monetary policy transmission (e.g., Bernanke and Blinder 1988, 1992; Jiménez et al. 2012; Scharfstein and Sunderam 2016; Altavilla et al. 2022) as well as the effects on bank stress tests (Acharya et al. 2018; Agarwal et al. 2020; Cortés et al. 2020; Sahin et al. 2020).

Finally, our work is related to the recent research showing that personal experiences influence the beliefs of sophisticated finance professionals, including central bankers (Malmendier et al. 2017), syndicated lenders (Koudijs and Voth 2016; Carvalho et al. 2022), and fund managers (Chernenko and Sunderam 2016). We add to this growing literature

[3] In terms of deposit-rate setting, Dlugosz et al. (2022) show that bank branches' ability to set deposit rates allow them to be more resilient to natural disasters. Drechsler et al. (2017) document that the response of deposit rates to monetary policy is influenced by local market competition. In the market for large corporate loans, Carvalho et al. (2022) find that loan officers' personal experiences matter for setting corporate loan spreads. (Kleiner et al. 2022) further document that bank entrepreneurs are driven by local opportunities. Scharfstein and Sunderam (2016) find that market competition affects mortgage lenders' responses to public market information. Yet, it is not clear whether such responses are determined at the headquarter of the bank or at the branch level.

by documenting that the decisions of bank branch managers are shaped by their past experiences with mortgage market outcomes.

2. Data and Sample

2.1. Data Sources

Our data come from several sources. First, we obtain information regarding bank branch managers and their career paths from the Revelio Labs. We then gather mortgage origination data from HMDA and supplement such information with interest rate, borrower characteristics such as credit score and loan performance data from CoreLogic. Finally, we construct measures of monetary policy shocks using data from the U.S. Department of the Treasury and Ken Kuttners' website.

To link the data on branch managers to mortgage information, we use bank names and identifiers from the Federal Reserve Call Reports as well as bank branch information from the FDIC.

2.2. Sample Construction

2.2.1. Bank Branch Managers Data

We collect information on the job histories of bank branch managers from Revelio Labs. Revelio provides detailed information regarding individuals' career trajectories, including individuals' name, job title, the name of the employer, the locations of the job, as well as the beginning and ending date of the job span. We start with a set of individuals that ever worked as bank branch managers at some point in their career. We then match the name of their employers to standardized bank name and identifiers (RSSDID) in the Call Report data provided by the Federal Reserve. After filtering out non-bank employers, we are left with 44,886 individuals who have worked in 27,199 bank branches. 32,378 job spans are associated with titles of "Branch Manager."

Importantly, we pin down the location of a job following several steps. First, some of the jobs are reported with detailed street address from Revelio Labs. In those cases, we directly extract the USPS 5-digit zipcode from those addresses. For some jobs, only MSA or state information is reported. For these incomplete addresses, we input the combination of bank names and broad location into Google Map, and extract the 5-digit USPS zipcode from the search results from Google Map. In this process, we require that the bank name is a good match to the ones returned from Google Map, and that the search returns fewer than 10 zipcodes.[4]

2.2.2. Mortgage Loans Data

Detailed information on mortgage loans comes from the Home Mortgage Disclosure Act (HMDA) and CoreLogic. For each loan, HMDA provides information including the location of the home purchased (refinanced), the lender of the loan, loan amount, as well as the denial or origination decision, etc. We link HMDAs' lender identifier to the Call Report identifier (RSSDID) using the bridge provided by Robert Avery. We also manually check the data for potentially missed matches.

However, HMDA does not contain data on interest rates charged for a mortgage prior to 2018. We supplement this information from CoreLogic. To do so, we follow a similar method as outlined by (DeFusco 2018) to match HMDA with CoreLogic. In HMDA, we focus on originated loans and not denied ones. In CoreLogic data, we focus on originated loans for home purchase, home improvement and refinancing and filter out all other loans like construction loan, medical loan, education loan, etc., so we can match this data with the same set of loan purposes stated in HMDA. Our matching procedure is based on the location of the loan (at the zipcode level), loan amount, the year of loan origination, loan purpose (home purchase, refinancing or home improvement), occupancy status (occupied by owner or not) and loan type (conventional or guaranteed loans). We define grids based on these characteristics and link loans in the two datasets within each grid. On average, each grid contains information from 2.4 originated loans in HMDA. The average interest rates for each grid from CoreLogic data is then assigned to all HMDA loans within the

[4]Given that our analysis is at the county level, we allow for multiple zipcodes being matched. We link zipcodes to county fips codes using the crosswalk file from $https://www.huduser.gov/portal/datasets/usps_crosswalk.html$. During the mapping process, we restrict one county has no more than 3 matches of 5-digit zipcodes and the resident ratio of matched zipcode is larger than 0.1. In the final sample, the average county is matched to 1.5 zipcodes.

same grid.

2.2.3. Testing Samples

Using our data on the job records of branch managers, we compile a manager-branch-year panel. A "branch" is identified as the combination of a bank-county pair. Given that our main empirical measure is managers' past job experiences, we restrict the sample only to observations where a previous job span can be observed for the manager. Our main analysis focuses on managers that have switched jobs over the sample period because we rely on their past job span to gauge personal experiences. This results in 178,547 manager-branch-year observations. In later robustness analysis, we provide an alternative testing strategy that utilizes all managers, including non-switchers.

Using this panel, we construct two testing samples. The first sample focuses on the denial rates of loan applications. We link each manager to all the loan applications filed to that branch during his job span, and compute denial rate as the percentage of applications denied for each branch-year. Our second sample is designed to analyze interest rates of originated loans. We connect each manager with the originated loans at their branch and consequently, the average interest rates charged on those loans.[5]

2.3. Measuring Manager Experience

Using the data sources above, we construct a manager-branch-year panel. We aggregate all loan (application)-level information to this panel by computing the average denial rates and average interest rates of loans in each branch-year. Similarly, we take the average of other loan-level characteristics such as loan-to-income ratio, percentage of different loan types like loans for home purchase, loans sold to other institutions, conventional loans, debt-to-income ratio, credit score, etc.

We are interested in how branch manager's experience with denial rates or interest rates from previous jobs. For each manager-branch, we trace back the manager's previous job in other branches, and compute the average denial rates and interest rates associated

[5]The denial rate sample consists more observations than the interest rate sample. This is because the former is constructed using HMDA data and the latter is based on the intersection of HMDA and CoreLogic data.

with the previous branch over the years that he/she worked in that branch.

In our analysis, we compare managers' experiences with the corresponding lending policy of their current branch in the recent past. Ideally, we should match the horizon during which we measure managers' past experiences and the policy of their current branch. Given that each manager has a different past job span, and there is no set "job span" for a branch, we compute branch-level past policies over the past three years. In later analysis, we show that results are robust if we use a 5-year window to define past branch decisions.

We compare a manager's past experience with the branch's past policies and define the difference as *Experience Gap*. This measure describes the extent to which the manager's experience deviates from the previous lending policies at the current branch, and also helps us differentiate the experience of the manager from the experience of other individuals in the same branch. Specifically, *Experience Gap* is defined as the following.

$$Experience\ Gap_{i,b,c,t}(R) = \bar{R}_{i,b',c',t'} - \bar{R}_{i,b,c,t}, \tag{1}$$

where R represents denial rate of loan applications or interest rate charged on originated loans, i is a manager, b a bank, c a county, and t a year. The pair of $\{b, c\}$ defines a branch. $\{b', c'\}$ represents the branch where manager i was employed prior to joining the current branch. $\bar{R}_{i,b',c',t'}$ is the average denial rate or interest rate at that branch over the time of the manager's employment. $\bar{R}_{i,b,c,t}$ is the average denial rate or interest rate at the current branch over the past three years.

Our main dependent variables are year-on-year changes in denial rate ($\Delta Denial\ Rate$) and changes in interest rate ($\Delta Interest\ Rate$) within a branch.

2.4. Summary Statistics

The average manager in our sample works in 2.57 jobs, and 2.39 jobs inside mortgage lenders. 58.19% of individuals have switched jobs. During a typical job switch, 2.25% of individuals switch across counties within the same bank, 72.02% of individuals change to a different bank inside the same county, and 25.73% of them switch both employers and locations.

Table 1 reports the summary statistics of the key variables used in our analysis. Panel A describes the sample for denial rate analysis, and Panel B provides summary of the sample for interest rate analysis. The average year-on-year change in denial rates is 0.2 percentage points, and the average manager's experience gap regarding denial rates is 0.9 percentage points. The average change in interest rate, however, is -15 basis points, consisting with the trend that mortgage rates have been declining over the past two decades. The experience gap of managers relative to the current branch is about 1 basis point.

The two samples have comparable statistics regarding loan characteristics, including loan-to-income ratio of around 2, percentage of home purchase loans to be around 34–40%. Around 8% of loans are guaranteed by a government entity. Local characteristics are also similar in both samples. The average population growth is around 7%, and the average county in our sample has 20% of minority population. Managers' average job span is 2.3 years.

Table 1 About Here

3. Manager Experience and Lending Policies

We examine the relation between branch manager experience gaps relative to their branch and the changes in denial rates and interest rates at their branch by estimating the following model:

$$\Delta R_{b,c,t} = \beta Experience\ Gap_{i,b,c,t}(R) + \boldsymbol{X}_{i,b,c,t} + \alpha_b + \gamma_c + \tau_t + \epsilon_{b,c,t}, \tag{2}$$

where i represents a manager, b represents a (parent) bank, c represents a county, and t represents a year. R is either denial rates of loan applications or interest rates charged on originated loans. $\boldsymbol{X}_{i,b,c,t}$ is a vector of controls, including loan, borrower, and county characteristics. Loan characteristics include the loan-to-income ratio across loans in a bank-county-year, the percentage of loans being sold, and the percentage of loans for home purchases. Borrower characteristics include the debt-to-income ratio and credit score of borrowers. County characteristics including population growth, the percentage of population that are minority, and personal income growth. We also control for manager tenure at the current branch.

Our dependent variable $\Delta R_{b,c,t}$ is the year-on-year changes in denial rate or interest rate at a bank branch. This first-difference approach helps absorb persistent characteristics of the bank branch. Thus, we do not control for bank-branch fixed effects in the regression. Instead, we control for bank fixed effects (α_b), county fixed effects (γ_c) and year fixed effects (τ_t). These fixed effects purge away confounding factors that are related to bank-specific traits, cross-county differences, and aggregate, macroeconomic conditions.

In stricter specifications, we also control for bank-year fixed effects, which remove any effect of policy or dynamic condition at the bank level. We further include the past average denial rate (or interest rate) for all the loan applications filed in the same county level over the past three years. This variable serves as a benchmark that captures the influence of local economic conditions that could affect denial rates or interest rates of mortgages. In other words, if any local conditions could affect bank lending policies, such conditions should affect all banks in the local area and will be captured by past county denial (interest) rate.

3.1. Main Results

Table 2 reports the main results of our paper from the estimation of Equation 2. Panel A reports the results for denial rates and Panel B reports the results for interest rates. In each panel, we present results with controls added in stages. In the first column, we examine the univariate relation between experience gap and changes in lending outcomes with no controls. Next, we add bank fixed effects and year fixed effects. In the third column, we further include continuous control variables, including loan, borrower, and county characteristics as well as county fixed effects. We next add county past denial rates or interest rates, and finally, we impose bank-year interactive fixed effects to absorb any bank-level conditions.

Table 2 About Here

Across all specifications and both outcome variables, we find strong, positive relation between branch managers' experience gap with the changes in current lending outcomes. Results from column (3), Panel A suggest that a one-standard deviation increase in the experience gap regarding denial rate (0.18) is associated with around a 3 percentage points increase in denial rate at the current branch. This is a large magnitude as it represents around 29% of the standard deviation of Δ*Denial Rate*. Similarly, our estimates from column (3), Panel B suggest that a one-standard-deviation increase in the interest rate experience gap (1.12) is associated with 4.3 basis points increase in the interest rates at the current branch, a 8% change relative to the sample standard deviation of dependent variable. Estimates from specifications with bank-year fixed effects are generally smaller, likely because we are limiting the comparison to managers in different branches at the same bank. From this strictest specification, a one-standard-deviation increase in experience gap is associated with a 1.9 percentage (basis) points higher denial (interest) rate.

Overall, our results indicate that managers' past experience influence their current lending decisions. These findings are consistent with the hypothesis that local branch managers have decision power, and as a result, their lending policies are shaped by relevant experiences in the past.

3.2. Event Study

In this section, we explore the dynamic influence of a new manager on the lending policies at the current branch. Specifically, we examine how denial rates and interest rates evolve over time at a branch before and after the arrival of a new manager, depending on his past experience. This analysis allows us to check whether denial rates or interest rates have increased prior to the manager's arrival. It also helps us gauge how soon rates are adjusted to reflect the manager's perceptions.

As a first step of the event study, we construct an event-by-branch sample. We gather all branch-year observations for which branches hire new managers, and compute the experience gap between the manager and the branch. These branches are then classified into two groups, one with positive experience gap and the other with negative experience gap. Within each group, we focus on branches where their new managers have distinctively large experience gaps, as this helps us better detect the managerial effects. Specifically, we consider a branch to be "treated" with a positive-experience-gap manager if the manager's experience gap ranks at the top tercile across all branches with positive rate gap managers. Treated branches with negative-experience-gap managers are defined accordingly. Among the treated group with positive experience gaps, the average branch has an *Experience Gap* of 27 percentage points for denial rates, and 1.6 percentage points for interest rates. Among those with negative experience gaps, the average branch has -29 percentage points gap for denial rates and -0.7 percentage points gap for interest rates.

We track each treated branch over the [-3, +3] years around its manager's arrival, and match it to branches that do not receive any new manager over our sample period. Through the matching, we seek to construct a control group consisting of bank branches that have similar size and lending standards to the treated branch. For each treated branch, we identify five nearest neighbors in terms of the total amount and number of loans issued as well as the denial (interest) rate of the branch. All matching characteristics are measured during the year prior to the event $(t-1)$. The resulting set of branches, including one treated and five control units, forms a match "group."

Based on the sign of the experience gap, we form four stacked event samples, two for denial rates and two for interest rates. For each outcome variable, we first stack all observations from the match groups with positive experiences gaps to construct samples with positive experience shocks. We expect denial (interest) rates to increase at treated branches relative to control branches in this sample. Analogously, we construct stacked samples with negative experience shocks, and expect rates to fall at treated branches after managers' arrival.

We estimate the following models using the stacked event sample:

$$R_{e,b,c,t} = \sum_{k=-3}^{3} \phi_k Treat^{+}_{e,b,c}(R) \times 1_{t=e_t+k} + \boldsymbol{X}_{b,c,t} + \theta_{b,c} + \eta_e + \tau_t + \epsilon_{e,b,c,t}, \tag{3}$$

$$R_{e,b,c,t} = \sum_{k=-3}^{3} \delta_k Treat^{-}_{e,b,c}(R) \times 1_{t=e_t+k} + \boldsymbol{X}_{b,c,t} + \theta_{b,c} + \eta_e + \tau_t + \epsilon_{e,b,c,t}, \tag{4}$$

where e represents an event (or a match group), e_t is the event year, and k represents years after the event year. $Treat^{+}_{e,b,c}$ is an indicator for whether branch $\{b, c\}$ receives a manager with a positive experience gap in year e_t. Similarly, $Treat^{-}_{e,b,c}$ indicates whether the branch receives a manager with a negative experience gap. We control for match group fixed effects (η_e), which allow us to compare a treated branch with its matched control branches. We also impose branch fixed effects ($\theta_{b,c}$) to track the same branch over the event window. We include all continuous controls as in the baseline specification, except manager tenure, because the unit of observation is no longer at the manager level. Standard errors are clustered by branch.

In this estimation, we are interested in coefficients $\{\phi_k\}$ and $\{\delta_k\}$, where k =-3,-2,..., 2, 3. Coefficients from the year prior to the event (θ_{-1} and δ_{-1}) are absorbed as the benchmark, so reported coefficients represent the level of denial rates or interest rates relative to the level in Year $e_t - 1$.

Figure 1 reports the dynamic effects for denial rates. Panel A depicts the changes in denial rates at branches with managers who experienced higher denial rates from the previous job. Panel B shows how denial rates evolve at branches with managers that experienced lower denial rates. We note that there is no significance change in denial rates prior to managers' arrival. Starting from the year of arrival, denial rates move in the same direction as managers' experience gap, increasing at branches with positive-gap managers and decreasing at ones with negative-gap managers. Such changes become statistically significant in the post-event years.

Figure 1 About Here

In Figure 2, we track interest rates at branches with new managers. Again, Panel A (B) presents the dynamic effects of positive-gap (negative-gap) managers on interest rates. Similar to the patterns from denial rates, we do not observe any significant increases or decreases in interest rate prior to the event. When a new manager with a high rate experience arrives at the branch, mortgage rates issued by the branch trends up, reaching a significantly higher level compared to the control group during the year after the event. Interest rates decline at branches that receive low-experience managers as well. Our estimates suggest that interest rates go up by 4.6 basis points following the arrival of positive-rate-gap managers, and go down by 11–15 basis points following negative-rate-gap ones. These effects do not revert in the three years following the event.

FIGURE 2 ABOUT HERE

Overall, results from the event study show that lending policies at the branch do not exhibit pre-event trends prior to managers' arrival. In particular, our analysis focuses on cases where managers have large experience gaps relative to the current branch. This helps address the concern that our baseline results may be capturing a labor market matching effect, i.e., branches that plan to increase denial rates or interest rates are more likely to recruit high-rate managers. These results are also informative of how managers adjust lending policies based on their beliefs or preferences. Importantly, such adjustments are not transient, but seem to persist under the managers' purview.

3.3. Effects of Experiences from Non-Manager Jobs

Our analysis so far documents that branch managers that have experienced high lending standards tend to raise the lending standards at their current branches. This finding can be interpreted as past experiences shaping managers' beliefs or preferences, or as managers implementing a fixed lending "style" consistently throughout their management career. While both interpretations imply that managers have some decision authority, they represent different mechanisms.

We evaluate whether our result at least partially reflects the effect of past experiences. To do so, we reconstruct the measure of manager past experiences using only denial rates and interest rates from past non-manager jobs. These positions include financial services officer, loan officer, teller, business advisor, etc. Individuals in those positions are unlikely to have authorities to fully determine the lending standards at a branch. Thus, this measure captures passive experiences regarding lending policies observed, but not controlled by individuals before they become managers in the current branches. If our findings are purely driven by managers imposing their personal, we should see the effects disappear when we look at non-management experiences. In Table 3, we find that these passive experiences have a strong, positive relation with changes in the lending outcomes at current branches. This results validate our interpretation that past experiences shape managerial decisions, and that our results are unlikely to be explained by managers' fixed characteristics or styles.

3.4. Demographic-Specific Experiences

Existing studies suggest that the effects of personal experiences tend to be "domain specific." When forming expectations, individuals tend to draw on experiences in related areas in the past. For example, (Kuchler and Zafar 2019) find that personal experiences related to housing prices only affect individuals' beliefs regarding future housing prices, but not their beliefs about future employment growth, and vice versa. Building on this view, we differentiate managers' experiences based on the demographics of borrowers. Specifically, we separately compute the average denial rates in a manager's past job span using applicants that are white male, female, and minority (i.e., nonwhite ethnicity), respectively. We also compute the average interest rates from borrowers in those demographic categories. These demographic-specific experiences are then related to the current lending policies for applicants (borrowers) of the same demographics.

Table 4 reports results from this analysis. Similar to Table 2, results on denial rates are reported in Panel A and results for interest rates are reported in Panel B. In each panel, we present results for white male (columns (1) and (2)), female (columns (3) and (4)), and minority (columns (5) and (6)), respectively. For each of these demographic groups, we first show results with bank, county, and year fixed effects, and then augment it with county past lending outcomes and bank-year fixed effects (following the specifications in column (3) and column (5) of Table 2).

Table 4 About Here

We continue to find *Experience Gap* to carry a significant, positive coefficient for the lending outcomes for each of the demographics. Moreover, the coefficients are generally larger than our base results. For example, a one-standard deviation increase in the experience gap regarding denial rate for minority applicants (0.239) is associated with around a 6.3 percentage points increase in denial rate for minority at the current branch. A same change in interest rate experience gap related to minority borrowers (1.193) is associated with around a 6.9 basis points change in the interest rates charged to minority at the current branch. These patterns are generally consistent with the idea that more relevant experiences tend to have a greater influence on current expectations and decision-making.

3.5. Heterogeneity Regarding Manager Discretion

Our results so far are consistent with the argument that managers' experiences shape their decision-making process. To substantiate this mechanism, we examine whether the effects of manager experiences become more pronounced in cases where managers are likely to have more discretion. Specifically, we test the heterogeneity of our effects across loans that embody higher and lower credit risk to lenders, across branches are farther or closer to the bank headquarter, and depending on whether an individual is the only manager in a bank-location.

3.5.1. Credit Risk

We first examine the role of credit risk in moderating our effects. To start, we compare the effects of manager experiences across conforming and non-conforming loans. Conforming loans are those that meet the underwriting standards of government-sponsored enterprises (GSE), and thus can be purchased by the enterprises. We expect managers' experiences to matter less for this type of loans, as lenders have the option to resell these loans and bear little credit risk. Interest rates on those loans are also heavily influenced by the secondary market. In contrast, nonconforming loans are riskier, harder to resell, and thus require substantial screening from lenders (Choi and Kim 2021). Managers' experiences or beliefs should have a greater influence over the origination and pricing decisions for nonconforming loans.

We next look into borrower characteristics and investigate how the effects vary across borrowers' credit score and income levels. Generally speaking, loans to low-credit-score borrowers and low-income borrowers are associated with higher credit risk and more difficult to resell. As a result, lenders have stronger incentives to conduct due diligence and screen borrowers (Keys et al. 2012). We define a borrower to have *Low Credit Score* if their credit score falls under 620. A borrower is classified to have *Low Income* if their income falls below the median across all loan applications in a year.

We test the above predictions by studying the differential effects of manager experiences across different types of loans. To do so, we dis-aggregate the branch-level lending outcomes by loan (borrower) types. For example, when studying the effect for conforming and non-conforming loans, we create two observations for each branch-year, one representing the interest rates charged for conforming loans by the branch, and the other capturing rates charged for non-conforming loans. Given that some of the above characteristics are available only for originated loans, such as conventional loans and borrowers' credit score, we focus our analysis on interest rates and not denial rates. We estimate the following model:

$$\begin{aligned}\Delta R_{b,c,l,t} = \beta_1 Experience\ Gap_{i,b,c,t}(R) + \beta_2 Experience\ Gap_{i,b,c,t}(R) \times 1_l \\ + X_{i,b,c,t} + \alpha_b + \gamma_c + \tau_t + \psi_l + \epsilon_{b,c,l,t}, \quad (5)\end{aligned}$$

where l represents a loan type (conforming or non-conforming loans, loans to low- or high-credit-score borrowers, and loans to high- or low-income borrowers). 1_l is an indicator for whether an observation belongs to a certain type. The regression controls for county, bank, and year fixed effects. In stricter specifications, we also add bank-by-year interactive fixed effects to narrow down the comparison within decisions made by different managers working in the same bank at the same point in time. We also include loan type fixed effects (ψ_l).

Table 5 shows the results from this analysis. Panel A reports the differential effects for low-income borrowers. We examine the effects on both denial rates and interest rates. Panel B reports the differential effects related to non-conforming loans and low-credit-score borrowers. Given that these characteristics are only available for originated loans, we only test the effects on interest rates, but not for denial rates. For simplicity, coefficients β_3 on loan type are not reported. For each partition, we first include county, bank, and year fixed effects, and then imposing county and bank-year fixed effects.

TABLE 5 ABOUT HERE

Across all loan type categories, we find the effect of manager past experiences to be more pronounced for non-conforming loans, loan-income borrowers, and low-credit-score borrowers. Such cross-sectional variation implies significant economic magnitudes. For example, our estimates from Panel B, Column (2) suggest that effects of manager experience on non-conforming loans are about 50% larger than the effects on conforming loans (= 0.009/0.02). Managers' past experiences also generate an impact on interest rate for low-credit-score borrowers that is over 70% greater than their impact on high-credit-score borrowers (= 0.03/0.04 from column (4)).

3.5.2. Market Discipline

We investigate the role of market discipline in moderating our effects. As managers form opinions based on their own experiences, such opinions may be less likely to translate into lending policies if they observe the denial rates and pricing of other lenders in the same market. In other words, the presence and the potential competition from other lenders in the local market may discipline manager actions and weaken their autonomy.

We thus assess the differential effects of manager experience based on the number of branch managers in the same county, as well as the concentration of lenders. Two variables are of interest. First, we define an indicator *Many Local Lenders*, which turns to one if the number of bank branch managers identified in a county during a year exceeds the sample median of this county-level manager counts. Second, we define the Herfindahl index (*Local Mortgage HHI*) of the local mortgage origination market share among all banks in a county. Lower values indicates a more competitive market, and thus managers should face a stronger market discipline.

We regress Δ*Denial Rate* and Δ*Interest Rate* on the interaction between *Experience Gap* and these two variables indicating market discipline. Table 6 reports the results. Panel A provides results for local lender counts, and Panel B presents results for local market HHI. Across both measures of market discipline and outcome variables, we find consistent evidence suggesting that managers' experience matters less for mortgage approval and deposit rate-setting in areas with stronger competitive market forces.

TABLE 6 ABOUT HERE

Taken together, our analysis suggests that the past experiences of managers generate a stronger effect on current lending policies in cases when managers have greater decision authority. Such evidence provides additional support for mortgage lending decisions being at least partially delegated to local branches.

4. Manager Experiences and Responses to Shocks

Our results so far suggest that managers can influence current lending policies based on past experiences. One concern related to such an interpretation is that our results may capture a manager fixed trait. For example, some managers may be intrinsically stricter than others, and they charge higher rates and deny more loans regardless of their place of employment. Another concern is that our results can be driven by dynamic manager-branch matching, whereby branches that seek to implement stricter policies may hire managers that have experiences with such policies.

We design two analyses to address these concerns, looking at the differential response to policy shocks across managers with heterogeneous experiences. In these analyses, we fix the manager-branch pair and trace how mortgage rates issued by the same branch under the same manager respond to shocks over time. This design helps eliminate the influence of manager fixed characteristics or manager-branch matching.

4.1. Monetary Policy Shocks

We examine how managers' past interest rate experiences affect the adjustment of mortgage rates to monetary policy shocks. This analysis can shed light on the "human factor" in the transmission and distributional effects of monetary policies. The literature on monetary policy transmission shows that monetary policies significantly affect consumer credit rates, including the residential mortgage rate (Ausubel 1990; Kahn et al. 2005; Scharfstein and Sunderam 2016). As documented by prior studies, following increases in federal funds rates, banks face higher funding costs and partially pass the rate hikes to households. Despite the prevalent evidence on the average passthrough effects, little is known regarding how the extent of the passthrough differs across bank branches, and whether individual managers could shape the transmission mechanism.

We expect past experiences with interest rates may amplify managers' responses to policy shocks that confirm their priors, but diminish their response to policy shocks in the opposite direction. To the extent that managers with high experience gaps may think the current branches' interest rates to be too low, they may be more likely to "agree" with policy shocks that tighten money supply and raise interest rates. In contrast, they may resist policy shocks that generate downward pressure on interest rates. To test this conjecture, we separate managers' experience gaps regarding interest rates into positive and negative ranges, and interact each of these experiences with tightening and loosening monetary shocks. We then estimate the response of mortgage rates to policy shocks under these four scenarios using the following model:

$$\Delta R_{b,c,t} = \beta_1 Experience\ Gap_{i,b,c,t}(R)^{+} \times 1^{MPS>0} + \beta_2 Experience\ Gap_{i,b,c,t}(R)^{-} \times 1^{MPS>0} + \beta_3 \times Experience\ Gap_{i,b,c,t}(R)^{+} \times 1^{MPS<0} + X_{i,b,c,t} + \alpha_b + \gamma_c + \theta_i + \epsilon_{b,c,t}, \quad (6)$$

where *Experience Gap*$^+$ is an indicator that equals to one when managers with positive interest rate experience gap, i.e., when managers' past experience involves interest rates that are higher than the rates at their current branches over the recent past, and zero otherwise. *Experience Gap*$^-$ turns to one when managers have negative interest experience gaps, and zero otherwise. $1^{MPS>0}$ and $1^{MPS<0}$ are indicators corresponding to positive and negative monetary policy shocks, respectively. We use two methods to construct monetary policy shocks. Our first measure uses the daily changes in the federal funds futures rate around FOMC announcements to measure monetary policy shocks following Kuttner (2001) and Bernanke and Kuttner (2005) and this measure capture the "surprise" component in the federal funds rate changes, which cannot be predicted by banks or managers ex ante. The second measure uses daily changes in the 10-year treasury yield rate.[6] Positive monetary shocks represent ones that increase banks' cost of funding, and negative shocks decrease banks' funding costs. In this estimation, $Experience\ Gap_{i,b,c,t}(R)^- \times 1^{MPS<0}$ is absorbed as the base scenario, and coefficients β_1, β_2, and β_3 represent incremental rate changes relative to that scenario.

Table 7 reports the results from the estimation of Equation (6). In column (1), we show the results from the base scenario, i.e., how interest rates respond to rate-decreasing monetary shocks when the branch manager has a negative experience gap regarding interest rates. Our estimates in Panel A suggest that interest rates on mortgages decrease by 35.9 basis points in this scenario. In this analysis, we control for bank and county fixed effects, together with all continuous controls used in the baseline analysis.

TABLE 7 ABOUT HERE

In column (2), we examine how the transmission of monetary policy shocks in other scenarios, compared to column (1). We first note that the coefficient of *Experience Gap*$^+ \times 1^{MPS<0}$ is positive and significant, suggesting that when managers have high-interest-rate experiences, they are less responsive to rate-decreasing monetary shocks. Similarly, the

[6]We aggregate the event day monetary policy surprises at an annual level. In Appendix A, we show that our results are robust when monetary policy shocks are measured using treasury bonds of maturities, including 2-year, 3-year, 5-year, and 20-year bonds.

coefficient of *Experience Gap*$^-$ $\times$ $1^{MPS>0}$ is also positive and significant, with similar magnitudes to the baseline response, i.e., coefficient of *Experience Gap*$^-$ $\times$ $1^{MPS<0}$. This indicates that when monetary shocks lead to pressures to increase mortgage rates, managers with low-interest-rate experiences are exhibit very little response, largely keeping rates unchanged. More importantly, we find that *Experience Gap*$^+$ $\times$ 1^{MPS+0} carries a large, positive coefficient, whose magnitude (0.5 in Panel A) exceeds the base effect. The estimate in Panel A suggests that in net, managers with high-interest-rate experiences raise mortgage rates by around 14 basis points ($= 0.499 - 0.359$) following rate-increasing monetary shocks.

In columns (3) through (6), we include more stringent fixed effects and controls to further alleviate concerns related to omitted variables. In columns (3) and (4), we add manager fixed effects, which allow us to compare how the same manager responds to different policy shocks as their experience evolve over time. This helps address the concern that our result may be capturing the intrinsic characteristics or preferences of an individual, or matching effects related to those characteristics. In column (6), we control for manager-branch pair fixed effects, which address issues related to dynamic matching related to managers' time-varying characteristics. Under the strictest specification, coefficient estimates are also slightly larger than those in column (2). Specifically, column (6) in Panel A suggests that managers with high-rate experiences raise mortgage rates by around 31 basis points ($= 0.667 - 0.359$) following rate-increasing monetary shocks. In contrast, managers whose experiences conflict with the direction of monetary shocks exhibit close to zero responses when setting mortgage rates. The results of using 10-year Treasury yield rate (reported in Panel B) are similar.

These results suggest that managers' prior experience with interest rates can shape their responses to monetary policy shocks. These effects are unlikely to be driven by a sorting story, i.e., banks that want to raise rates in the future choose to recruit a manager who is more experienced in high-rate environments. This is because the monetary policy shocks are unexpected by either the bank or the manager ex ante.

Given that we are extrapolating managers' *Experience Gap* using their entire employment history, one concern is that this measurement can be contaminated by the aggregate decline of interest rates throughout our sample period. Indeed, as reported in Panel A of Figure 3, over 80% of the manager-branch-years are associated with positive interest rate *Experience Gap* while only less than 20% have negative gaps. To alleviate this concern, we construct a new variable, *Experience Gap (Adjusted)*, by first demeaning the branch-level interest rate by the annual average mortgage rate. We then use this demeaned branch-level interest rate to construct a manager's experience gap following Equation (1). The redefined *Experience Gap (Adjusted)* allows us to compare across managers that have experienced higher or lower interest rates over the same time period in the past.

We repeat the analysis in Table 7 using the adjusted experience measure and report the results in Table 8. We continue to find that managers with experiences consistent with monetary policy rate shocks respond strongly to the policy, which those with conflicting experiences resist policy changes. Estimates from column (6) in Panel A suggest that managers with high-interest-rate experiences raise mortgage rates by around 28 basis points ($= 0.512 - 0.235$) following positive monetary shocks.

TABLE 8 ABOUT HERE

Taken together, our results show that monetary policies generate the strongest pass-through when branches hire managers with positive experience gaps and subsequently encounter a rate-increasing shock, or when branches hire managers with negative experience gaps and encounter a rate-reducing shock. In these cases, the shocks confirm the managers' prior regarding the direction of the interest rate changes—for example, a positive *Experience Gap* manager would deem the current interest rate as being "too low." As a positive policy shock pushes banks to raise the interest rates, such a shock confirms his prior and he is more likely to implement such changes. In cases when the managers' prior conflicts with the direction of the policy shock, their reaction to the shock becomes much more muted.

4.2. Stress Tests

We next look into how mortgage rates at each branches respond to stress test results, depending on the past experiences of their managers. After the Global Financial Crises, bank regulators in many countries started implementing stress tests, which measure the amount of losses a bank must endure under severe economic downturns and the capital reserve needed to survive. Failure to pass stress tests means that banks need to reduce the risks in their asset portfolio and/or improve capital adequacy. A growing literature documents that stress test failures are associated with changes in credit decisions by banks across various markets. Such changes include reduced credit supply to riskier borrowers and higher rates charged to those borrowers (e.g., Acharya et al. 2018, Kohn and Liang 2019, Cortés et al. 2020).

We collect data on the outcome of stress tests from the Comprehensive Capital Analysis and Review (CCAR) conducted by the Federal Reserve. For banks that failed the stress test, we expect them to raise lending standards by increasing mortgage rates as well as denial rates. The extent of such adjustments may differ across branches depending on branch managers' experiences. To test this conjecture, we focus on a list of 39 large bank holding companies that have undergone the stress tests, and create indicators for whether a bank passed the test (1^{Pass}) or failed the test (1^{Fail}) in a year. We then apply the same framework as outlined in Equation 6, while switching the indicators for the directions of monetary shocks with indicators of whether banks passed or failed the stress tests. In this analysis, we look at both changes in denial rates and interest rates as our outcome variables. When measuring managers' interest rate experiences, we focus on the adjusted experiences as there are limited observations when banks that failed stress tests hired managers whose un-adjusted rate experience gaps take negative values.

Results are reported in Table 9. Panel A reports results regarding changes in denial rates. In column (1), we show that when banks have passed stress tests, managers with low denial rate experiences reduce their denial rates (or, increase their approval rates) by 3.3 percentage points. Results from column (2) through (6) report the differential responses of loan denial rates when stress test results conform or conflict with managers' experiences. When banks fail to pass stress tests, managers that have experiences with stricter lending standards increase denial rates by around 3.5 percentage points ($= 6.729 - 3.341$). This effect weakens when managers have a low-denial-rate experience. For banks that pass stress tests, managers with high-denial-rate experiences still deny more loans, but only by around 3.0 percentage points ($= 6.202 - 3.341$).

<u>Table 9 About Here</u>

Panel B present results on interest rates. Similar to the previous analyses, we first regress changes in interest rates on an indicator for whether a bank holding company fails the stress test. We find a significant, positive coefficient, indicating that managers with low-interest-rate experiences cut rates by around 18 basis points when their bank holding companies have passed stress tests. We then analyze rate changes under other scenarios depending on managers' interest rate experiences as well as banks' stress test results. However, when managers have high-interest-rate experiences, they raise interest rate by around 14 basis points ($= 0.318 - 0.175$) despite the passage of stress tests. When banks fail stress tests, interest rates increase substantially under managers with high-rate experiences, by around 15 basis points ($= 0.327 - 0.175$), but stays largely unchanged when managers have low-rate experiences.

We next present coefficients on the interaction between managers' adjusted experience gaps and indicators for whether banks passed or failed stress tests. We add fixed effects and control variables in stages, following the same format as in Table 8. Across all specifications, we find positive coefficients on $Experience\ Gap^{+} \times 1^{Fail}$, suggesting that mortgage rates increase significantly more in branches with managers with high-rate experiences when the bank fails a stress test. In contrast, the coefficient for $Experience\ Gap^{-} \times 1^{Fail}$ is not statistically different from zero, indicating that managers with low-rate experiences are resilient to the pressure to raise mortgage rates.

5. Borrower Characteristics and Loan Performance

Can managers' experience-driven lending decisions explained by the credit risk of their borrowers? If managers with higher rate experiences are matched with applicant pools that are inherently riskier, their lending standards could be a response to credit risk, not a result of personal experience effects.

We assess this possibility using two analyses. First, we examine whether observable characteristics of borrowers are correlated with managers' past experiences. Specifically, for each bank-county, we compute the percentage of applicants that are female or minority, the average income of the applicants, as well as the average credit score. In Appendix C, we do not find any significant correlation between borrower characteristics and managers' past experiences, either with interest rates or denial rates.

Second, we examine the ex post performance of originated loans. If managers with high rate experiences are matched with riskier borrowers, we might observe a differential default or delinquency rates from the loans they originate. We consider a loan to be delinquent if it appears in at least one of the following four categories: (1) late payments by 60 days, (2) late payments by over 90 days, (3) foreclosure, and (4) real estate owned. At a bank branch level, delinquency rate is computed as the percentage of all the loans originated in a year that end up delinquent. In Table 10, we find that branches with high-experience-gap managers do not exhibit higher delinquency rates than branches with low-experience-gap managers. If anything, high-experience-gap managers are associated with slightly lower delinquency rate, consistent with these managers imposing a stricter lending standard. In Appendix D, we test the correlation between manager experiences with each of the four delinquency categories and do not find a meaningful relation with any of these categories.

Table 10 About Here

6. Additional Robustness

We design several additional analyses to test the robustness of our results to various empirical choices such as sample selection and measurements.

One concern with our measure of experience gap is that the horizon at which we measure managers' past experiences may not line up with the horizon of branches' past lending policy. Recall that managers' past experiences are based on all the years the managers worked at their previous employers, while branches' past lending policies are based on the past three years. To address this concern, we measure managers' past experiences also using the past three years as well. This helps align the measurement horizon of managers' and branches' past lending experience, and could purge away macroeconomic or local effects that shape mortgage market outcomes.

In this analysis, we consider the full sample of all managers, regardless of whether they have changed jobs in the past. Managers that did not switch jobs have an experience gap of zero by construction. They thus serve as a "control" group. We repeat Equation 2 while switching *Experience Gap* using managers' past 3 years of experience. Table 11 reports the results. Panel A reports the summary statistics of experience gaps as well as the changes in denial rates and interest rates across all branches. Note that the standard deviation of experience gaps become smaller than the one in the baseline sample (Table 1). This is because experience gap equals zero for a substantial fraction of the sample. Panel B (C) reports results for changes in denial (interest) rate at the current branch. We continue to find a significant, positive relation between managers' experience gap with changes in lending policies at the current branch.

<u>TABLE 11 ABOUT HERE</u>

Next, we consider the possibility that managers' past experiences may become stale as they work for a longer period of time in the current institution, or that managers may adjust to the new norm over time. We thus perform a robustness test by restricting the sample to only the first three years of managers' tenure at the current branch. Table 12 shows that our main findings persist, and the coefficients remain similar to those in the baseline results.

TABLE 12 ABOUT HERE

Relatedly, we evaluate whether experiences accumulated earlier in a manager's career matter more or less compared to more recent experiences. On the one hand, early-career experiences may generate an imprinting effect and shape individual cognition and behaviors in the long run (e.g., Malmendier and Nagel 2011; Bernile et al. 2017; Malmendier et al. 2011). On the other hand, individuals tend to overweight recent experiences and form their expectations disproportionately based on recent economic conditions (e.g., Bordalo et al. 2019; Bordalo et al. 2022). Following (Malmendier and Nagel 2011), we define a parameter δ indicating the "depreciation" rate on past experiences, and assign a weight for experiences in a previous year τ as $(1-\delta)^{-(t-\tau)}$, where t indicates the current year. Suppose the depreciation rate is 0.5, experiences in the prior year are half as important as current experiences, and those two years ago are only a quarter as important. We repeat our baseline analysis for $\delta = 0.25, 0.5, 0.75$. Table 13 shows that our results are robust to discounting prior-year experiences. Regardless of the depreciation rate, managers' past experiences are significantly associated with current lending policies. Interestingly, as we increase the depreciation rate, coefficients become slightly weaker, highlighting the importance of early-career experiences. This result is consistent with prior academic evidence that early-career experiences shape managerial decisions in profound ways.

TABLE 13 ABOUT HERE

7. Conclusion

The recent decades have witnessed a fast expansion of the banking industry across U.S. geographies. While theories predict substantial benefits from delegating decision right to local branches, empirical evidence on this front remains scant. This paper investigates whether mortgage lending decisions are delegated to local bank branches. The mortgage market serves as a desirable setting to examine this question, as it is composed of large, geographically disperse lenders and highly localized borrowers.

We study this question by compiling a unique dataset featuring a broad set of bank branch manager. Our data link the lending decisions at their branches throughout their career histories. Using this data, we trace managers' personal experiences with mortgage approval and pricing at their past places of employment. We find that these past experiences influence their subsequent lending standards even after they switch employments across firms and locations. Such effects are particularly pronounced in cases where managers have greater discretion. Importantly, past experiences with interest rates influence the way local branches respond to monetary shocks. Responses to rate-increasing shocks are amplified when managers also have experienced higher rate environments. Similarly, rate-reducing shocks are followed by greater reductions in mortgage rates by managers with low-rate experiences. When monetary shocks contradict managers' experiences, mortgage rates display a muted response.

This study is the first to provide micro-level evidence in support of the delegation of decision rights to local branches within banking institutions. Critically, we find that the personal experiences of managers significantly impact their decisions, even such experiences are idiosyncratic and not informative of the current market conditions. These results shed light on the relevance of the "human factor" in the decision chain inside modern banking organizations.

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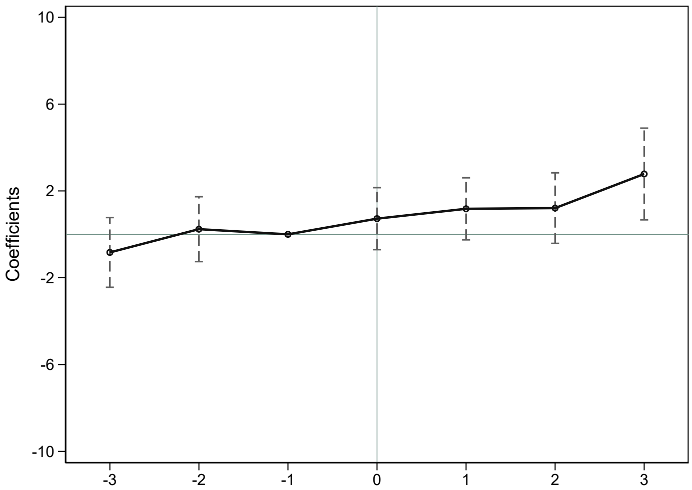
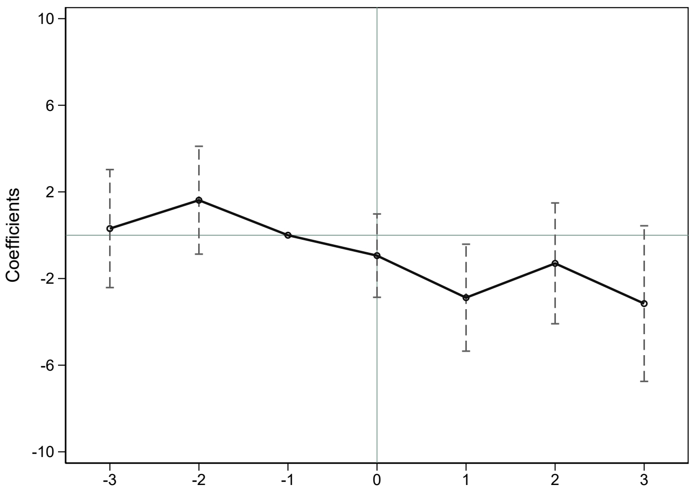
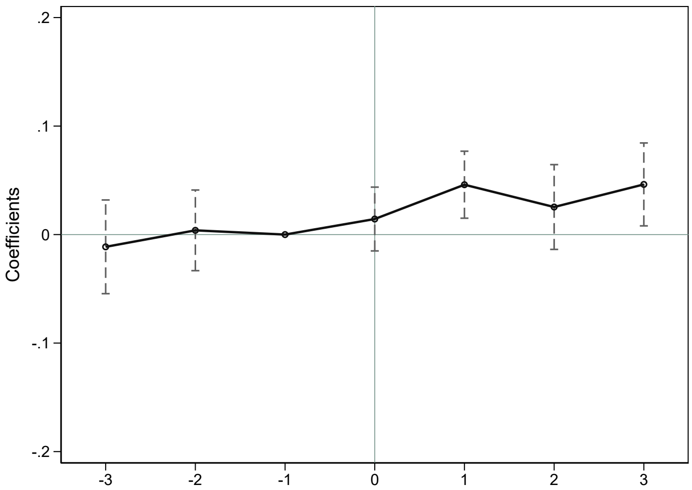


Panel A: Denial Rates for Managers with Positive Experience Gaps (Manager − Branch)

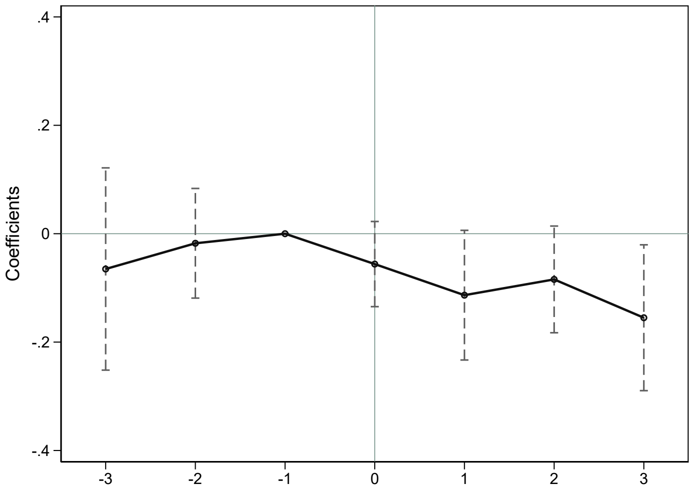


Panel B: Denial Rates for Managers with Negative Experience Gaps (Manager − Branch)

Figure 1. Dynamic Effects on Denial Rate
This figure shows the changes of denial rates at a branch before and after the joining of a new manager. Panel A reports the results when the new manager has higher denial rate experience relative to the current branch (i.e., positive *Experience Gap*). Panel B reports the results when the new manager has lower denial rate experience relative to the current branch (i.e., negative *Experience Gap*). Within each panel, we match "treated" branches to five nearest neighbors of control branches based on their branch size (the amount and count of loans issued) and denial rates, measured during the year prior to the event. Treated branches with positive denial rate gaps are defined as ones that hire new managers with positive denial rate gaps, and the managers' experience gaps rank at the top tercile across all such branches. Treated branches with negative denial rate gaps are defined analogously. Control branches are sampled from all branches that never hire a new manager during our sample period. In each panel, the dots represent coefficient estimates and the dashed lines represent the 90% confidence interval.

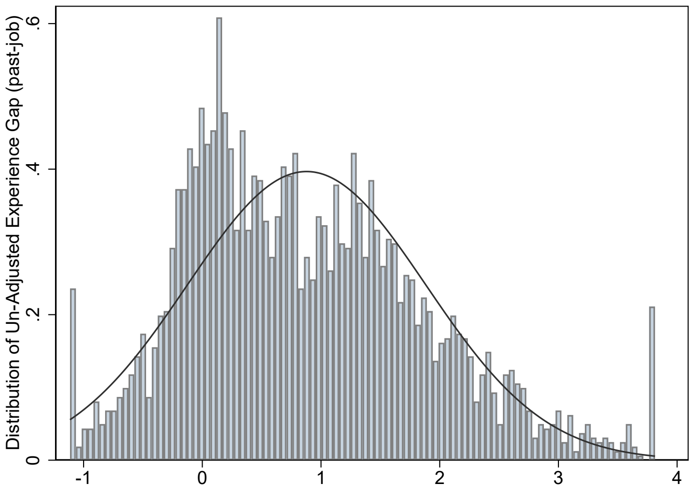


Panel A: Interest Rates for Managers with Positive Experience Gaps

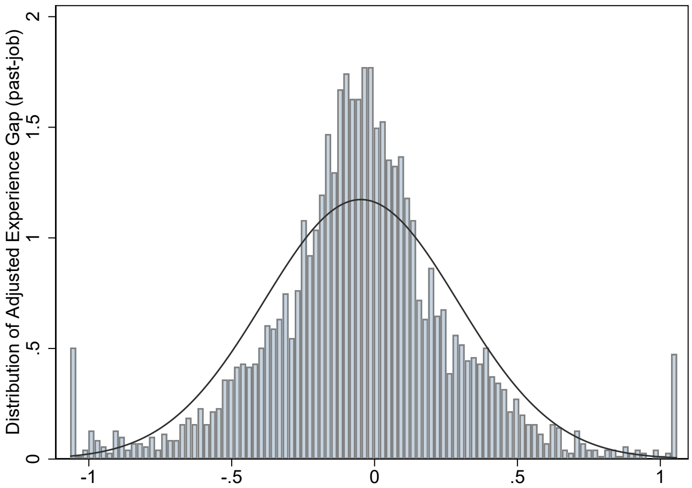


Panel B: Interest Rates for Managers with Negative Experience Gaps

Figure 2. Dynamic Effects on Interest Rate
This figure shows the changes of interest rates at a branch before and after the joining of a new manager. Panel A reports the results when the new manager has higher interest rate experience relative to the current branch (i.e., positive *Experience Gap*). Panel B reports the results when the new manager has lower interest rate experience relative to the current branch (i.e., negative *Experience Gap*). Within each panel, we match "treated" branches to five nearest neighbors of control branches based on their branch size (the amount and count of loans issued) and denial rates, measured during the year prior to the event. Treated branches with positive interest rate experience gaps are defined as ones that hire new managers with positive interest rate gaps, and the managers' experience gaps rank at the top tercile across all such branches. Treated branches with negative rate gaps are defined analogously. Control branches are sampled from all branches that never hire a new manager during our sample period. In each panel, the dots represent coefficient estimates and the dashed lines represent the 90% confidence interval.



Panel A: Distribution for Experience Gap constructed by Un-adjusted Interest Rates



Panel B: Distribution for Experience Gap constructed by Adjusted Interest Rates

Figure 3.
This figure shows the distribution of manager's experience gap. Panel A reports the results when the experience gap is constructed by using un-adjusted interest rates. Panel B reports the results when the experience gap is constructed by using adjusted interest rates.

Table 1. Summary Statistics
This table presents the summary statistics for the key variables used in our analysis. Our sample includes 10,263 banker managers working in 6,619 bank branches. The sample spans the period from 1990 through 2017.

Panel A: Denial Rate Sample

Variables	N	Mean	SD	P25	P50	P75
Denial Rate (%)	8,108	24.620	15.920	12.980	23.060	33.580
Δ*Denial Rate (%)*	8,108	0.171	10.490	-4.137	0.000	4.498
Experience Gap	8,108	0.859	18.110	-10.830	0.287	12.080
County Past Denial Rate	8,108	23.960	6.011	19.610	23.590	27.610
Loan-to-Income	8,063	2.137	0.808	1.637	2.064	2.544
%Sold Loans	8,108	32.780	23.380	13.240	31.640	50.250
%Home Purchase	8,108	34.770	20.110	20.000	32.000	47.610
%Refinancing	8,108	49.480	20.840	34.830	49.610	64.420
%Guaranteed Loans	8,108	7.939	11.240	0.000	3.465	11.110
Population Growth (%)	8,108	7.447	24.710	0.250	0.876	1.751
%Minority Population	8,108	21.860	13.350	11.850	19.210	29.710
Personal Income Growth (%)	7,994	4.167	3.509	2.390	4.286	6.180
Manager Tenure	8,108	2.291	2.646	0.000	1.000	3.000

Panel B: Interest Rate Sample

Variables	N	Mean	SD	P25	P50	P75
Interest Rate (%)	6,663	4.770	1.193	3.875	4.266	5.663
Δ*Interest Rate (%)*	6,663	-0.154	0.527	-0.475	-0.209	0.254
Experience Gap	6,663	1.009	1.116	0.101	0.840	1.756
County Past Interest Rate	6,663	5.150	1.258	4.010	4.696	6.148
Loan-to-Income	6,652	2.298	0.607	1.907	2.238	2.622
%Sold Loans	6,663	55.510	30.620	33.330	61.700	80.650
%Home Purchase	6,663	39.090	25.170	18.940	36.800	56.520
%Refinancing	6,663	60.590	25.120	43.330	62.640	80.570
%Guaranteed Loans	6,663	8.484	13.300	0.000	2.418	11.540
Debt-to-Income	6,550	34.530	4.727	32.070	34.710	37.160
LTV	6,663	71.650	9.813	65.950	72.240	78.060
Credit Score	6,649	737.100	27.590	722.000	743.600	756.800
Population Growth (%)	6,663	7.679	25.220	0.234	0.830	1.682
%Minority Population	6,663	22.080	13.240	12.280	19.280	29.910
Personal Income Growth (%)	6,576	4.126	3.388	2.390	4.272	6.115
Manager Tenure	6,663	2.315	2.660	0.000	1.000	3.000

Table 2. Manager Experiences and Current Lending Policies

This table reports the effect of managers' past experience gap on the changes in the lending policies at the current branch. The sample period is 1990 – 2017. The sample includes all managers that have switched jobs in the past. The unit of observations is a manager-branch-year. Branch is defined as the combination of a bank (RSSD ID) and a county. The key variable of interest is *Experience Gap*, measured as the average denial (interest) rates across loan applications (loans) at the past employer of a manager minus the average denial (interest) rates at the current branch over the past three years. Panel A reports the results for denial rates. The dependent variable is the year-on-year changes in loan application denial rates at the current branch. Panel B reports results for interest rates. The dependent variable is the year-on-year changes in interest rates charged on issued loans at the current branch. Detailed variable definitions are provided in Appendix A. *Controls* include the loan-to-income ratio, % of sold loans, % of loans for home purchase in a bank-county-year, the debt-to-income ratio and credit score of borrowers, and county characteristics including population growth, % of minority population, and personal income growth, and manager tenure. County past denial rates or interest rates are computed as the average over the past three years. Standard errors are double clustered by manager and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Denial Rate (%)

Dep. Var: Δ*Denial Rate*	(1)	(2)	(3)	(4)	(5)
Experience Gap, Denial Rate	0.086***	0.111***	0.166***	0.164***	0.103***
(*Manager – Branch*)	(0.007)	(0.012)	(0.017)	(0.017)	(0.015)
Controls			Yes	Yes	Yes
County FE			Yes	Yes	Yes
Bank FE		Yes	Yes	Yes	
Year FE		Yes	Yes	Yes	
County Past Denial Rate				Yes	Yes
Bank-Year FE					Yes
Observations	8,108	8,006	7,789	7,789	6,022
R-squared	0.022	0.116	0.220	0.222	0.489

Panel B: Interest Rate (%)

Dep. Var: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)
Experience Gap, Interest Rate	0.086***	0.019***	0.038***	0.028***	0.017***
(*Manager – Branch*)	(0.007)	(0.003)	(0.006)	(0.005)	(0.005)
Controls			Yes	Yes	Yes
County FE			Yes	Yes	Yes
Bank FE		Yes	Yes	Yes	
Year FE		Yes	Yes	Yes	
County Past Interest Rate				Yes	Yes
Bank-Year FE					Yes
Observations	6,663	6,577	6,326	6,326	4,934
R-squared	0.033	0.782	0.819	0.826	0.889

Table 3. Robustness: Experiences from Non-Manager Jobs

This table reports results from a robustness analysis of Table 2. The sample includes branch managers that have switched from a non-manager job to branch manager. The unit of observations is a manager-branch-year. Branch is defined as the combination of a bank (RSSD ID) and a county. The key variable of interest is *Experience Gap*, measured as the average denial (interest) rates across loan applications (loans) at the past employer of a manager minus the average denial (interest) rates at the current branch over the past three years. Panel A reports the results for denial rates. The dependent variable is the year-on-year changes in loan application denial rates at the current branch. Panel B reports results for interest rates. The dependent variable is the year-on-year changes in interest rates charged on issued loans at the current branch. Detailed variable definitions are provided in Appendix A. Control variables are defined in the same way as Table 2. Standard errors are double clustered by manager and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Denial Rate (%)

Dep. Var: Δ*Denial Rate*	(1)	(2)	(3)	(4)	(5)
Experience Gap, Denial Rate	0.073***	0.105***	0.152***	0.150***	0.095***
$(Manager - Branch)$	(0.010)	(0.010)	(0.016)	(0.016)	(0.015)
Controls			Yes	Yes	Yes
County FE			Yes	Yes	Yes
Bank FE		Yes	Yes	Yes	
Year FE		Yes	Yes	Yes	
County Past Denial Rate				Yes	Yes
Bank-Year FE					Yes
Observations	6,865	6,781	6,601	6,601	5,030
R-squared	0.017	0.134	0.223	0.225	0.511

Panel B: Interest Rate (%)

Dep. Var: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)
Experience Gap, Interest Rate	0.081***	0.017***	0.032***	0.024***	0.013***
$(Manager - Branch)$	(0.007)	(0.003)	(0.005)	(0.004)	(0.004)
Controls			Yes	Yes	Yes
County FE			Yes	Yes	Yes
Bank FE		Yes	Yes	Yes	
Year FE		Yes	Yes	Yes	
County Past Interest Rate				Yes	Yes
Bank-Year FE					Yes
Observations	5,611	5,546	5,316	5,316	4,091
R-squared	0.036	0.804	0.840	0.848	0.913

Table 4. Effects of Manager Experiences by Demographic

This table reports results from a robustness analysis of Table 2 while separating the experiences and lending outcomes for borrower demographics. We look at loans to white male, female, and nonwhite borrowers separately. The sample includes all managers that have switched jobs in the past. The unit of observations is a manager-branch-year. The key variable of interest is *Experience Gap*, measured as the average denial (interest) rates across loan applications (loans) at the past employer of a manager minus the average denial (interest) rates at the current branch over the past three years. Panel A reports the results for changes in denial rates. Panel B reports results for changes in interest rates. In each panel, columns (1) and (2) report results for loans to white male borrowers. *Experience Gap* is measured based on past loans issued to white male borrowers only. Columns (3) and (4) report results for loans to female borrowers. *Experience Gap* is measured based on past loans issued to female borrowers only. Columns (5) and (6) report results for loans to nonwhite borrowers. *Experience Gap* is measured based on past loans issued to nonwhite borrowers only. Detailed variable definitions are provided in Appendix A. Control variables are defined in the same way as in Table 2. Standard errors are double clustered by manager and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Denial Rate (%)

Sample:	White Male		Female		Minority	
Dep. Var: Δ*Denial Rate*	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap, Denial Rate	0.229***	0.148***	0.244***	0.167***	0.264***	0.200***
($Manager - Branch$)	(0.022)	(0.019)	(0.024)	(0.021)	(0.023)	(0.025)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
County Past Denial Rates		Yes		Yes		Yes
Bank-Year FE		Yes		Yes		Yes
Observations	7,542	5,822	7,214	5,619	7,197	5,573
R-squared	0.210	0.461	0.198	0.441	0.196	0.412

Panel B: Interest Rate (%)

Sample:	White Male		Female		Minority	
Dep. Var: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap, Interest Rate	0.046***	0.022***	0.057***	0.028***	0.058***	0.020***
($Manager - Branch$)	(0.006)	(0.005)	(0.010)	(0.007)	(0.011)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
County Past Interest Rates		Yes		Yes		Yes
Bank-Year FE		Yes		Yes		Yes
Observations	5,994	4,680	5,447	4,272	4,936	3,920
R-squared	0.789	0.875	0.703	0.807	0.673	0.794

Table 5. The Effects of Credit Risk

This table reports the heterogeneous effect of managers' past experience gap on the current lending policies across loan types. The sample period is 1990 – 2017. The sample includes all managers that have switched jobs in the past. The unit of observations is a manager-branch-year. Branch is defined as the combination of a bank (RSSD ID) and a county. The key variable of interest is *Experience Gap*, measured as the average interest rates across loans at the past employer of a manager minus the average interest rates at the current branch over the past three years. Column (1) and (2) in Panel A report the results across borrowers for denial rates. The dependent variable is the year-on-year changes in loan application denial rates at the current branch. Column (3) and (4) in Panel A and Panel B reports results across borrowers and loan types for interest rates. The dependent variable is the year-on-year changes in interest rates charged on issued loans at the current branch. Loan types include non-conforming loans, loans to low-credit-score borrowers, and loans to low-income borrowers. *Low Credit Score* is an indicator for whether the borrowers' credit score is below 620. *Low Income* indicates whether borrowers' income is below the sample median for a given year. Detailed variable definitions are provided in Appendix A. Control variables are defined in the same way as in Table 2. Standard errors are double clustered by manager and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Differential Effects Across Borrowers

Dep. Var:	Δ*Denial Rate*		Δ*Interest Rate*	
Borrower Type: Low Income	(1)	(2)	(3)	(4)
Experience Gap × *Borrower Type*	-0.008	-0.004	0.006**	0.007***
	(0.012)	(0.012)	(0.003)	(0.002)
Experience Gap	0.191***	0.150***	0.042***	0.028***
	(0.019)	(0.019)	(0.006)	(0.005)
Borrower Type	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Bank FE	Yes		Yes	
Year FE	Yes		Yes	
Bank-Year FE		Yes		Yes
Observations	16,656	16,349	11,551	11,218
R-squared	0.192	0.439	0.783	0.854

Panel B: Differential Effects Across Loan Characteristics

Loan Type:	Non-Conforming		Low Credit Score	
Dep. Var: Δ*Interest Rate*	(1)	(2)	(3)	(4)
Experience Gap × *Loan Type*	0.013**	0.009*	0.033***	0.030***
	(0.005)	(0.005)	(0.009)	(0.009)
Experience Gap	0.027***	0.020***	0.048***	0.040***
	(0.005)	(0.004)	(0.007)	(0.006)
Loan Type	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Bank FE	Yes		Yes	
Year FE	Yes		Yes	
Bank-Year FE		Yes		Yes
Observations	8,912	7,880	8,401	7,419
R-squared	0.794	0.859	0.656	0.738

Table 6. The Effects of Market Discipline

This table reports the heterogeneous effect of managers' past experience gap on the current lending policies across different counties. The sample period is 1990 – 2017. The sample includes all managers that have switched jobs in the past. The unit of observations is a manager-branch-year. Panel A reports the moderating role of *Many Local Lenders*, which is an indicator equal to one if the number of bank managers in a county-year exceeds the sample median. Panel B reports the role of *Local Mortgage HHI*, the Herfindahl index of mortgage origination volume across lenders in a county-year. In each Panel, Columns (1) and (2) report the results for denial rates, and Columns (3) and (4) report results for interest rates. Detailed variable definitions are provided in Appendix A. Control variables are defined in the same way as in Table 2. Standard errors are double clustered by manager and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: The Number of Local Lenders

Dep. Var:	Δ*Denial Rate*		Δ*Interest Rate*	
	(1)	(2)	(3)	(4)
Experience Gap $\times$ *Many Local Lenders*	-0.056***	-0.052***	-0.025***	-0.005
	(0.020)	(0.020)	(0.007)	(0.006)
Experience Gap	0.190***	0.128***	0.048***	0.015**
	(0.019)	(0.019)	(0.008)	(0.006)
Many Local Lenders	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
County FE		Yes	Yes	Yes
Bank FE	Yes		Yes	
Year FE	Yes		Yes	
Bank-Year FE		Yes		Yes
Observations	8,715	6,780	7,000	5,464
R-squared	0.211	0.492	0.816	0.894

Panel B: Local Market Competition

Dep. Var:	Δ*Denial Rate*		Δ*Interest Rate*	
	(1)	(2)	(3)	(4)
Experience Gap $\times$ *Local Mortgage HHI*	0.052**	0.053***	0.019***	0.008*
	(0.021)	(0.018)	(0.007)	(0.005)
Experience Gap	0.134***	0.073***	0.024***	0.009**
	(0.016)	(0.012)	(0.005)	(0.004)
Local Mortgage HHI	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Bank FE	Yes		Yes	
Year FE	Yes		Yes	
Bank-Year FE		Yes		Yes
Observations	8,715	6,780	7,000	5,464
R-squared	0.211	0.492	0.816	0.894

Table 7. Responses to Monetary Policy Shocks

This table reports the heterogeneous effect of managers' past experience gap on the current lending policies across loan types. The sample period is 1990 – 2017. The sample includes all managers that have switched jobs in the past. The unit of observations is a manager-branch-year. Branch is defined as the combination of a bank (RSSD ID) and a county. In Panel A, we use the daily changes in the federal funds futures rate around FOMC announcements to measure monetary policy shocks following Kuttner (2001) and Bernanke and Kuttner (2005). In Panel B, we use the daily changes in 10-year treasury yield rate to measure monetary policy shock. $1^{MPS>0}$ is an indicator for positive monetary policy shocks and $1^{MPS<0}$ indicates negative shocks. *Experience Gap*$^+$ is an indicator for whether a manager's experience gap is positive, i.e., the manager's past experience involves interest rates that is higher than the current branch's level over the past three years. *Experience Gap*$^-$ represents negative experience gaps. The dependent variable is the year-on-year changes in interest rates charged on issued loans at the current branch. In this analysis, we drop year fixed effects so the coefficients of monetary policy shocks are not absorbed. Detailed variable definitions are provided in Appendix A. Control variables are defined in the same way as in Table 2. Standard errors are double clustered by manager and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Test using Federal Fund Future

Dep. Var.: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap$^-$ $\times$ $1^{MPS<0}$	-0.359***		-0.406***		-0.404***	
	(0.034)		(0.051)		(0.043)	
Experience Gap$^+$ $\times$ $1^{MPS>0}$		0.499***		0.632***		0.667***
		(0.037)		(0.063)		(0.054)
Experience Gap$^-$ $\times$ $1^{MPS>0}$		0.367***		0.285***		0.295***
		(0.061)		(0.076)		(0.060)
Experience Gap$^+$ $\times$ $1^{MPS<0}$		0.240***		0.382***		0.409***
		(0.032)		(0.064)		(0.056)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes				
Manager FE			Yes	Yes		
Manager-Branch FE					Yes	Yes
Observations	3,023	3,023	2,643	2,643	2,565	2,565
R-squared	0.551	0.583	0.626	0.651	0.623	0.649

Panel B: Test using 10-Year Treasury Yield Rate

Dep. Var.: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap$^-$ $\times$ $1^{MPS<0}$	-0.427***		-0.504***		-0.507***	
	(0.036)		(0.054)		(0.045)	
Experience Gap$^+$ $\times$ $1^{MPS>0}$		0.742***		0.876***		0.919***
		(0.032)		(0.055)		(0.049)
Experience Gap$^-$ $\times$ $1^{MPS>0}$		0.701***		0.629***		0.619***
		(0.052)		(0.092)		(0.079)
Experience Gap$^+$ $\times$ $1^{MPS<0}$		0.159***		0.302***		0.338***
		(0.026)		(0.052)		(0.046)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes				
Manager FE			Yes	Yes		
Manager-Branch FE					Yes	Yes
Observations	3,023	3,023	2,643	2,643	2,565	2,565
R-squared	0.567	0.725	0.641	0.763	0.638	0.763

Table 8. Responses to Monetary Policy Shocks, Adjusted Interest Rate Experience

This table reports how managers respond differently to monetary policy shocks based on their adjusted past experience. When calculating experiences with interest rates from past jobs, we subtract the annual average mortgage interest rates from each year of experience. This helps address the concern that interest rates may follow a time trend over our sample. The sample period is 1990 – 2017. The sample includes all managers that have switched jobs in the past. The unit of observations is a manager-branch-year. Branch is defined as the combination of a bank (RSSD ID) and a county. This table reports the response of mortgage rates to monetary policy rates based on managers' adjusted interest rate experiences. The measurement of monetary policy shock, the definition of dummy variables $1^{MPS>0}$ and $1^{MPS<0}$ are the same as in Table 7. *Experience Gap*$^+$ is an indicator for whether a manager's experience gap is positive, i.e., the manager's past experience involves adjusted interest rates that is higher than the current branch's level over the past three years. *Experience Gap*$^-$ represents negative experience gaps (measured with adjusted interest rate). The dependent variable is the year-on-year changes in interest rates charged on issued loans at the current branch. In this analysis, we drop year fixed effects so the coefficients of monetary policy shocks are not absorbed. Detailed variable definitions are provided in Appendix A. Control variables are defined in the same way as in Table 2. Standard errors are double clustered by manager and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Test using Federal Fund Future

Dep. Var.: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap$^- \times 1^{MPS<0}$	-0.235***		-0.247***		-0.250***	
	(0.028)		(0.040)		(0.031)	
Experience Gap$^+ \times 1^{MPS>0}$		0.414***		0.471***		0.512***
		(0.036)		(0.076)		(0.065)
Experience Gap$^- \times 1^{MPS>0}$		0.284***		0.260***		0.259***
		(0.031)		(0.040)		(0.032)
Experience Gap$^+ \times 1^{MPS<0}$		0.065**		0.148**		0.182***
		(0.026)		(0.057)		(0.048)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes				
Manager FE			Yes	Yes		
Manager-Branch FE					Yes	Yes
Observations	3,023	3,023	2,643	2,643	2,565	2,565
R-squared	0.541	0.573	0.621	0.641	0.621	0.640

Panel B: Test using 10-Year Treasury Yield Rate

Dep. Var.: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap$^- \times 1^{MPS<0}$	-0.415***		-0.490***		-0.511***	
	(0.021)		(0.032)		(0.026)	
Experience Gap$^+ \times 1^{MPS>0}$		0.738***		0.850***		0.894***
		(0.033)		(0.064)		(0.058)
Experience Gap$^- \times 1^{MPS>0}$		0.611***		0.599***		0.599***
		(0.022)		(0.036)		(0.029)
Experience Gap$^+ \times 1^{MPS<0}$		0.096***		0.214***		0.257***
		(0.019)		(0.049)		(0.046)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes				
Manager FE			Yes	Yes		
Manager-Branch FE					Yes	Yes
Observations	3,023	3,023	2,643	2,643	2,565	2,565
R-squared	0.605	0.724	0.684	0.762	0.687	0.761

Table 9. Responses to Stress Tests

This table reports how managers respond differently to stress tests based on their past experience (denial rate in Panel A and interest rate in Panel B). The calculation of experience for denial rate is same as the Panel A in 2, and the calculation of experience for interest rate is same as 8. The sample period is 2013 – 2017. The sample includes all managers that have switched jobs in the past. The unit of observations is a manager-branch-year. Branch is defined as the combination of a bank (RSSD ID) and a county. We use the stress test data in CCAR to define banks of failing stress tests following (Cortés et al. 2020). 1^{Fail} is an indicator for whether the bank holding company fails the stress test and 1^{Pass} indicates the bank passing stress tests. The definition of *Experience Gap*$^+$ and *Experience Gap*$^-$ are the same as Table 8. The dependent variable in Panel A (B) is the year-on-year changes in denial (interest) rates at the current branch. In this analysis, we drop year fixed effects so we can compare branches' responses to different stress test shocks (fail or pass). Detailed variable definitions are provided in Appendix A. Control variables are defined in the same way as in Table 2. Standard errors are double clustered by manager and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Effects on Denial Rate

Dep. Var.: Δ*Denial Rate*	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap$^- \times 1^{Pass}$	-3.341***		-8.382*		-7.565**	
	(1.005)		(4.701)		(3.475)	
Experience Gap$^+ \times 1^{Fail}$		6.729***		9.933		8.629
		(1.505)		(6.560)		(4.886)
Experience Gap$^+ \times 1^{Pass}$		6.202***		6.544**		6.251**
		(1.852)		(2.729)		(2.233)
Experience Gap$^- \times 1^{Fail}$		3.286***		8.629		7.746*
		(1.032)		(5.150)		(3.815)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes				
Manager FE			Yes	Yes		
Manager-Branch FE					Yes	Yes
Observations	756	756	639	639	633	633
R-squared	0.351	0.353	0.426	0.426	0.433	0.433

Panel B: Effects on Interest Rate

Dep. Var.: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap$^- \times 1^{Pass}$	-0.175***		-0.374		-0.387**	
	(0.053)		(0.211)		(0.164)	
Experience Gap$^+ \times 1^{Fail}$		0.327***		0.540*		0.559**
		(0.072)		(0.265)		(0.206)
Experience Gap$^+ \times 1^{Pass}$		0.318***		0.215**		0.211***
		(0.100)		(0.079)		(0.062)
Experience Gap$^- \times 1^{Fail}$		0.162**		0.428		0.449**
		(0.057)		(0.253)		(0.194)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes				
Manager FE			Yes	Yes		
Manager-Branch FE					Yes	Yes
Observations	631	631	523	523	521	521
R-squared	0.360	0.362	0.443	0.445	0.442	0.445

Table 10. Manager Experiences and Loan Performance

This table reports the effect of managers' past experience gap on the loan performance at the current branch. The sample period is 1990 – 2017. The sample includes all managers that have switched jobs in the past. The unit of observations is a manager-branch-year. Branch is defined as the combination of a bank (RSSD ID) and a county. The dependent variable in Panel A and Panel B is the branch-level annual default rate (in %) which calculated from CoreLogic Loan Performance dataset. A mortgage loan is defined as delinquent when the loan is identified with following four conditions: (i) 60 days late payments as defined by the Office of Thrift Supervision (OTS), (ii) 90+ days late payments as defined by OTS, (iii) in foreclosure, or (iv) real estate owned (REO). The delinquency rate of a bank branch is the number of loans originated in a given year by the bank branch that end up delinquent divided by the number of originated loans by the branch in that year. Other variable definitions are the same as in Table 2. Standard errors are double clustered by manager and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Delinquency Rate and Manager Experience Gap Regarding Denial Rate

Dep. Var: *Delinquency Rate*	(1)	(2)	(3)	(4)	(5)
Experience Gap, Denial Rate	-0.000	-0.006***	-0.004	-0.005*	-0.003
(*Manager – Branch*)	(0.005)	(0.002)	(0.003)	(0.003)	(0.003)
Controls			Yes	Yes	Yes
County FE			Yes	Yes	Yes
Bank FE		Yes	Yes	Yes	
Year FE		Yes	Yes	Yes	
County Past Denial Rate				Yes	Yes
Bank-Year FE					Yes
Observations	7,163	7,066	6,906	6,906	5,357
R-squared	0.000	0.594	0.722	0.726	0.833

Panel B: Delinquency Rate and Manager Experience Gap Regarding Interest Rate

Dep. Var: *Delinquency Rate*	(1)	(2)	(3)	(4)	(5)
Experience Gap, Interest Rate	-0.626***	0.045	-0.079	-0.096	0.069
(*Manager – Branch*)	(0.143)	(0.073)	(0.128)	(0.128)	(0.125)
Controls			Yes	Yes	Yes
County FE			Yes	Yes	Yes
Bank FE		Yes	Yes	Yes	
Year FE		Yes	Yes	Yes	
County Past Interest Rate				Yes	Yes
Bank-Year FE					Yes
Observations	6,665	6,579	6,326	6,326	4,934
R-squared	0.006	0.548	0.706	0.706	0.794

Table 11. Robustness: Past Three Years of Experience, All Manager Sample
This table reports results from a robustness analysis of Table 2. The sample includes all managers that have or have not switched jobs in the past. The unit of observations is a manager-branch-year. Branch is defined as the combination of a bank (RSSD ID) and a county. The key variable of interest is *Experience Gap*, measured as the past-three-year average denial (interest) rates across loan applications (loans) at the past employer of a manager minus the average denial (interest) rates at the current branch over the past three years. Panel A reports summary statistics for the dependent and independent variables in this test. Panel B reports the results for denial rates. The dependent variable is the year-on-year changes in loan application denial rates at the current branch. Panel C reports results for interest rates. The dependent variable is the year-on-year changes in interest rates charged on issued loans at the current branch. Detailed variable definitions are provided in Appendix A. Control variables are defined in the same way as Table 2. Standard errors are double clustered by manager and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Summary Statistics

Variables	N	Mean	SD	P25	P50	P75
Experience Gap (Denial Rate)	30,932	0.113	4.060	0.000	0.000	0.000
Experience Gap (Interest Rate)	26,453	0.000	0.060	0.000	0.000	0.000
Denial Rate (%)	30,932	23.360	16.530	11.710	20.730	31.820
Δ*Denial Rate* (%)	30,932	0.223	10.320	-3.779	0.000	4.286
Interest Rate (%)	26,453	5.186	1.425	3.973	4.631	6.290
Δ*Interest Rate* (%)	26,453	-0.175	0.580	-0.541	-0.210	0.255

Panel B: Denial Rate (%)

Dep. Var: Δ*Denial Rate*	(1)	(2)	(3)	(4)	(5)
Experience Gap, Denial Rate	0.111***	0.101***	0.107***	0.105***	0.081***
(*Manager* − *Branch*)	(0.026)	(0.027)	(0.023)	(0.023)	(0.019)
Controls			Yes	Yes	Yes
County Past Denial Rates				Yes	Yes
County FE			Yes	Yes	Yes
Bank FE		Yes	Yes	Yes	
Year FE		Yes	Yes	Yes	
Bank-Year FE					Yes
Observations	30,932	30,792	30,246	30,246	25,596
R-squared	0.002	0.058	0.116	0.118	0.426

Panel C: Interest Rate (%)

Dep. Var: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)
Experience Gap, Interest Rate	0.217***	0.116***	0.080**	0.087**	0.072**
(*Manager* − *Branch*)	(0.083)	(0.036)	(0.035)	(0.034)	(0.034)
Controls			Yes	Yes	Yes
County Past Interest Rates				Yes	Yes
County FE			Yes	Yes	Yes
Bank FE		Yes	Yes	Yes	
Year FE		Yes	Yes	Yes	
Bank-Year FE					Yes
Observations	26,453	26,351	25,371	25,371	21,461
R-squared	0.001	0.771	0.804	0.812	0.884

Table 12. Robustness: Effects of Experiences During First Three Years on the Job
This table reports results from a robustness analysis of Table 2. The sample includes branch managers that have switched jobs in the past and we only keep the first 3-year working records in the current ban branch. The unit of observations is a manager-branch-year. Branch is defined as the combination of a bank (RSSD ID) and a county. The key variable of interest is *Experience Gap*, measured as the average denial (interest) rates across loan applications (loans) at the past employer of a manager minus the average denial (interest) rates at the current branch over the past three years. Panel A reports the results for denial rates. The dependent variable is the year-on-year changes in loan application denial rates at the current branch. Panel B reports results for interest rates. The dependent variable is the year-on-year changes in interest rates charged on issued loans at the current branch. Detailed variable definitions are provided in Appendix A. Control variables are defined in the same way as Table 2. Standard errors are double clustered by manager and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Denial Rate (%)

Dep. Var: Δ*Denial Rate*	(1)	(2)	(3)	(4)	(5)
Experience Gap, Denial Rate	0.087***	0.109***	0.150***	0.147***	0.095***
$(Manager - Branch)$	(0.009)	(0.013)	(0.018)	(0.018)	(0.017)
Controls			Yes	Yes	Yes
County Past Denial Rates				Yes	Yes
County FE			Yes	Yes	Yes
Bank FE		Yes	Yes	Yes	
Year FE		Yes	Yes	Yes	
Bank-Year FE					Yes
Observations	6,230	6,118	5,951	5,951	4,473
R-squared	0.020	0.131	0.252	0.254	0.517

Panel B: Interest Rate (%)

Dep. Var: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)
Experience Gap, Interest Rate	0.096***	0.026***	0.036***	0.027***	0.012**
$(Manager - Branch)$	(0.009)	(0.005)	(0.007)	(0.006)	(0.005)
Controls			Yes	Yes	Yes
County Past Interest Rates				Yes	Yes
County FE			Yes	Yes	Yes
Bank FE		Yes	Yes	Yes	
Year FE		Yes	Yes	Yes	
Bank-Year FE					Yes
Observations	5,090	5,000	4,809	4,809	3,649
R-squared	0.030	0.783	0.822	0.828	0.894

Table 13. Robustness: Depreciating Earlier Job Experiences

This table reports results where we utilize all of managers' job experiences and apply a depreciation rate for experiences accumulated in each of the preceding years. We use three depreciation rate ($\delta = 0.25, 0.5, 0.75$) when computing past experience. Specifically, we use a weight for experience in year τ that is $(1-\delta)^{t-\tau}$, where t is the current year of observations. The sample includes all managers that have switched jobs in the past. The unit of observations is a manager-branch-year. The key variable of interest is *Experience Gap*, measured as the average denial (interest) rates across loan applications (loans) at the past employer of a manager minus the average denial (interest) rates at the current branch over the past three years. Panel A reports the results for changes in denial rates. Panel B reports results for changes in interest rates. Detailed variable definitions are provided in Appendix A. Control variables are defined in the same way as in Table 2. Standard errors are double clustered by manager and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Denial Rate (%)

Depreciation rate:	$\delta = 0.75$		$\delta = 0.50$		$\delta = 0.25$	
Dep. Var: Δ*Denial Rate*	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap, Denial Rate	0.148***	0.092***	0.166***	0.105***	0.182***	0.115***
($Manager - Branch$)	(0.015)	(0.013)	(0.016)	(0.014)	(0.017)	(0.015)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
County Past Denial Rates		Yes		Yes		Yes
Bank-Year FE		Yes		Yes		Yes
Observations	8,715	6,780	8,715	6,780	8,715	6,780
R-squared	0.209	0.490	0.213	0.492	0.216	0.493

Panel B: Interest Rate (%)

Depreciation rate:	$\delta = 0.75$		$\delta = 0.50$		$\delta = 0.25$	
Dep. Var: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap, Interest Rate	0.028***	0.011***	0.033***	0.012***	0.038***	0.014***
($Manager - Branch$)	(0.005)	(0.004)	(0.006)	(0.004)	(0.007)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
County Past Interest Rates		Yes		Yes		Yes
Bank-Year FE		Yes		Yes		Yes
Observations	7,000	5,464	7,000	5,464	7,000	5,464
R-squared	0.815	0.894	0.815	0.894	0.816	0.894

Appendix A. Variable Definitions

- *Denial Rate*: The average rate of loan applications being denied by a branch (bank-county) in a year.
- *Experience Gap*: The average denial (interest) rates across loan applications (loans) at the past employer of a manager minus the average denial (interest) rates at the current branch over the past three years.
- *Loan-to-Income*: The ratio of loan amount and loan applicant's income for each loan application.
- *%Sold Loans*: For all originated loans approved by a bank branch in a year, the percentage of loans being sold to other institutions such as Fannie Mae, Freddie Mac or commercial banks.
- *%Home Purchase*: For all loan applications submitted to a bank branch in a year, the percentage of loan applications with the stated loan purpose for home purchase.
- *%Refinancing*: For all loan applications submitted to a bank branch in a year, the percentage of loan applications with the stated loan purpose for Refinancing.
- *%Guaranteed Loans*: For all loan applications submitted to a bank branch in a year, the percentage of loan applications being insured or guaranteed by government institutions such as FHA, VA, etc.
- *Debt-to-Income*: Total of all debt payments including the new mortgage payment (principal, interest, insurance and taxes, (PITI)) divided by the gross monthly income of the borrower(s).
- *LTV*: Original Loan To Value. Original mortgage amount divided by the lesser of the origination appraised value or the sales price.
- *Credit Score*: Borrower's FICO credit score at the time of origination used for underwriting.
- *Population Growth*: The county-level growth rate of total population.
- *% Minority Population*: The percentage of minority people (all non-white ones) in the whole population of a county.
- *Personal Income Growth*: The growth rate of personal income for a county.
- *Manager Tenure*: Number of work years for a manager working in current bank branch.
- *Non-conforming*: An indicator variable that equals to one if the originated loans are not purchased by the GSEs but held in bank portfolios or sold to private investors, zero otherwise.
- *Low Credit Score*: An indicator variable that equals to one if originated loans with borrower's FICO credit score less than 620, zero otherwise.
- *Low Income*: An indicator variable that equals to one if originated loans with borrower's income below the median income of all loan applications in a year, zero otherwise.
- *Experience Gap*$^+$: An indicator variable that equals to one if the manager's past-job experience on denial (interest) rates is higher than current branch's past three-year experience on denial (interest) rate, and zero otherwise.
- *Experience Gap*$^-$: An indicator variable that equals to one if the manager's past-job experience on denial (interest) rates is lower than current branch's past three-year experience on denial (interest) rate, and zero otherwise.
- $1^{MPS>0}$: An indicator variable that equals to one if the unexpected changes/surprises in Federal Fund future rate is greater than 0, and zero otherwise.

- $1^{MPS<0}$: An indicator variable that equals to one if the unexpected changes/surprises in Federal Fund future rate is lower than 0, and zero otherwise.
- 1^{Fail}: An indicator variable that equals to one if the bank didn't pass the stress test, and zero otherwise.
- 1^{Pass}: An indicator variable that equals to one if the bank passed the stress test, and zero otherwise.
- *Default Rate*: The number of default loans divided by the number of originated loans in each year for a bank branch. A mortgage loan is defined as "default" when the loan is identified with following four conditions: (i) 60 days late payments as defined by the Office of Thrift Supervision (OTS), (ii) 90+ days late payments as defined by OTS, (iii) in foreclosure, or (iv) real estate owned (REO).

Appendix B. Monetary Policy Transmission, Additional Tests

Table B1. Responses to Monetary Policy Shocks

This table reports the heterogeneous effect of managers' past experience gap on the current lending policies across loan types. The sample period is 1990 – 2017. The sample includes all managers that have switched jobs in the past. The unit of observations is a manager-branch-year. Branch is defined as the combination of a bank (RSSD ID) and a county. We use the daily changes in the 2-year, 3-year, 5-year and 20-year Treasury yield rate to measure monetary policy shocks in Panel A, B, C and D, respectively. The empirical setting and variable construction are the same as in Table 7. Standard errors are double clustered by manager and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Test using 2-Year Treasury Yield Rate

Dep. Var.: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)	(6)
$Experience\ Gap^{-} \times 1^{MPS<0}$	-0.461***		-0.535***		-0.543***	
	(0.044)		(0.068)		(0.058)	
$Experience\ Gap^{+} \times 1^{MPS>0}$		0.743***		0.892***		0.971***
		(0.042)		(0.061)		(0.054)
$Experience\ Gap^{-} \times 1^{MPS>0}$		0.663***		0.839***		0.853***
		(0.064)		(0.200)		(0.175)
$Experience\ Gap^{+} \times 1^{MPS<0}$		0.214***		0.312***		0.352***
		(0.034)		(0.055)		(0.045)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes				
Manager FE			Yes	Yes		
Manager-Branch FE					Yes	Yes
Observations	3,023	3,023	2,643	2,643	2,565	2,565
R-squared	0.559	0.644	0.635	0.700	0.632	0.700

Panel B: Test using 3-Year Treasury Yield Rate

Dep. Var.: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)	(6)
$Experience\ Gap^{-} \times 1^{MPS<0}$	-0.398***		-0.418***		-0.411***	
	(0.040)		(0.058)		(0.049)	
$Experience\ Gap^{+} \times 1^{MPS>0}$		0.642***		0.749***		0.781***
		(0.035)		(0.059)		(0.054)
$Experience\ Gap^{-} \times 1^{MPS>0}$		0.523***		0.389***		0.377***
		(0.062)		(0.099)		(0.083)
$Experience\ Gap^{+} \times 1^{MPS<0}$		0.176***		0.313***		0.341***
		(0.030)		(0.052)		(0.046)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes				
Manager FE			Yes	Yes		
Manager-Branch FE					Yes	Yes
Observations	3,023	3,023	2,643	2,643	2,565	2,565
R-squared	0.557	0.650	0.631	0.695	0.628	0.692

Panel C: Test using 5-Year Treasury Yield Rate

Dep. Var.: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap$^{-} \times 1^{MPS<0}$	-0.424***		-0.494***		-0.495***	
	(0.035)		(0.054)		(0.045)	
Experience Gap$^{+} \times 1^{MPS>0}$		0.737***		0.869***		0.910***
		(0.031)		(0.054)		(0.048)
Experience Gap$^{-} \times 1^{MPS>0}$		0.683***		0.597***		0.587***
		(0.052)		(0.093)		(0.080)
Experience Gap$^{+} \times 1^{MPS<0}$		0.157***		0.298***		0.334***
		(0.026)		(0.050)		(0.044)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes				
Manager FE			Yes	Yes		
Manager-Branch FE					Yes	Yes
Observations	3,023	3,023	2,643	2,643	2,565	2,565
R-squared	0.566	0.723	0.640	0.761	0.637	0.760

Panel D: Test using 20-Year Treasury Yield Rate

Dep. Var.: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap$^{-} \times 1^{MPS<0}$	-0.421***		-0.505***		-0.508***	
	(0.035)		(0.055)		(0.046)	
Experience Gap$^{+} \times 1^{MPS>0}$		0.675***		0.729***		0.751***
		(0.035)		(0.058)		(0.053)
Experience Gap$^{-} \times 1^{MPS>0}$		0.667***		0.634***		0.621***
		(0.052)		(0.088)		(0.070)
Experience Gap$^{+} \times 1^{MPS<0}$		0.261***		0.357***		0.378***
		(0.030)		(0.053)		(0.047)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes				
Manager FE			Yes	Yes		
Manager-Branch FE					Yes	Yes
Observations	3,023	3,023	2,643	2,643	2,565	2,565
R-squared	0.567	0.647	0.641	0.696	0.638	0.694

Table B2. Responses to Monetary Policy Shocks Using Adjusted Interest Rate
This table reports how managers respond differently to monetary policy shocks based on their adjusted past experience. When calculating experiences with interest rates from past jobs, we subtract the annual average mortgage interest rates from each year of experience. This helps address the concern that interest rates may follow a time trend over our sample. The sample period is 1990 – 2017. The sample includes all managers that have switched jobs in the past. The unit of observations is a manager-branch-year. Branch is defined as the combination of a bank (RSSD ID) and a county. This table reports the response of mortgage rates to monetary policy rates based on managers' adjusted interest rate experiences. We use the daily changes in the 2-year, 3-year, 5-year and 20-year Treasury yield rate to measure monetary policy shocks in Panel A, B, C and D, respectively. The empirical setting and variable construction are the same as in Table 8. Standard errors are double clustered by manager and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Test using 2-Year Treasury Yield Rate

Dep. Var.: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)	(6)
$Experience\ Gap^{-} \times 1^{MPS<0}$	-0.390***		-0.482***		-0.493***	
	(0.027)		(0.053)		(0.044)	
$Experience\ Gap^{+} \times 1^{MPS>0}$		0.686***		0.848***		0.921***
		(0.034)		(0.065)		(0.057)
$Experience\ Gap^{-} \times 1^{MPS>0}$		0.579***		0.654***		0.673***
		(0.031)		(0.057)		(0.047)
$Experience\ Gap^{+} \times 1^{MPS<0}$		0.086***		0.193***		0.216***
		(0.022)		(0.055)		(0.048)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes				
Manager FE			Yes	Yes		
Manager-Branch FE					Yes	Yes
Observations	3,023	3,023	2,643	2,643	2,565	2,565
R-squared	0.568	0.640	0.646	0.697	0.644	0.696

Panel B: Test using 3-Year Treasury Yield Rate

Dep. Var.: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)	(6)
$Experience\ Gap^{-} \times 1^{MPS<0}$	-0.358***		-0.387***		-0.395***	
	(0.023)		(0.041)		(0.033)	
$Experience\ Gap^{+} \times 1^{MPS>0}$		0.604***		0.659***		0.700***
		(0.032)		(0.062)		(0.057)
$Experience\ Gap^{-} \times 1^{MPS>0}$		0.496***		0.453***		0.449***
		(0.028)		(0.047)		(0.037)
$Experience\ Gap^{+} \times 1^{MPS<0}$		0.086***		0.183***		0.224***
		(0.021)		(0.049)		(0.047)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes				
Manager FE			Yes	Yes		
Manager-Branch FE					Yes	Yes
Observations	3,023	3,023	2,643	2,643	2,565	2,565
R-squared	0.575	0.646	0.649	0.690	0.648	0.687

Panel C: Test using 5-Year Treasury Yield Rate

Dep. Var.: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap$^{-} \times 1^{MPS<0}$	-0.414***		-0.485***		-0.505***	
	(0.020)		(0.032)		(0.026)	
Experience Gap$^{+} \times 1^{MPS>0}$		0.735***		0.845***		0.889***
		(0.032)		(0.063)		(0.058)
Experience Gap$^{-} \times 1^{MPS>0}$		0.606***		0.590***		0.590***
		(0.022)		(0.036)		(0.028)
Experience Gap$^{+} \times 1^{MPS<0}$		0.096***		0.213***		0.256***
		(0.019)		(0.048)		(0.046)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes				
Manager FE			Yes	Yes		
Manager-Branch FE					Yes	Yes
Observations	3,023	3,023	2,643	2,643	2,565	2,565
R-squared	0.605	0.722	0.683	0.760	0.686	0.759

Panel D: Test using 20-Year Treasury Yield Rate

Dep. Var.: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap$^{-} \times 1^{MPS<0}$	-0.301***		-0.365***		-0.383***	
	(0.021)		(0.034)		(0.027)	
Experience Gap$^{+} \times 1^{MPS>0}$		0.549***		0.599***		0.639***
		(0.036)		(0.063)		(0.055)
Experience Gap$^{-} \times 1^{MPS>0}$		0.469***		0.431***		0.428***
		(0.025)		(0.034)		(0.027)
Experience Gap$^{+} \times 1^{MPS<0}$		0.078***		0.180***		0.226***
		(0.022)		(0.054)		(0.049)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes				
Manager FE			Yes	Yes		
Manager-Branch FE					Yes	Yes
Observations	3,023	3,023	2,643	2,643	2,565	2,565
R-squared	0.567	0.632	0.653	0.686	0.654	0.685

Appendix C. Manager Experience and Borrower Characteristics

Table C1. Composition Change of Loan Applicants and Manager Experience
This table reports results of investigating the relation between composition change of loan applicants and manager's past experience gap. The unit of observations is a manager-branch-year. Branch is defined as the combination of a bank (RSSD ID) and a county. The key variable of interest is *Experience Gap*, measured as the average denial (interest) rates across loan applications (loans) at the past employer of a manager minus the average denial (interest) rates at the current branch over the past three years. Panel A reports the results for denial rates. Panel B reports results for interest rates. The dependent variable in column (1) and (2) of each panel is the year-on-year changes in the percentage of female or minority applicants which from HMDA database.. The dependent variable in column (3) and (4) of each panel is the year-on-year changes in the loan applicant's income which from HMDA database. The dependent variable in column (5) and (6) in Panel B is the year-on-year changes in the loan applicant's credit score which from CoreLogic database. Detailed variable definitions are provided in Appendix A. Standard errors are double clustered by manager and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Relation with Experience Gap of Denial Rate

Dep. Var:	Δ % of Female or Minority		Δ Applicant Income	
	(1)	(2)	(3)	(4)
Experience Gap	0.001	-0.003	0.269	0.330
	(0.012)	(0.012)	(0.192)	(0.208)
County FE	Yes	Yes	Yes	Yes
Bank FE	Yes		Yes	
Year FE	Yes		Yes	
Bank-Year FE		Yes		Yes
Observations	6,683	5,049	6,812	5,144
R-squared	0.132	0.392	0.122	0.208

Panel B: Relation with Experience Gap of Interest Rate

Dep. Var:	Δ % of Female or Minority		Δ Applicant Income		Δ Credit Score	
	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap	0.444	0.369	-1.445	-1.187	-0.327	-0.144
	(0.303)	(0.360)	(1.049)	(1.257)	(0.313)	(0.243)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
Bank-Year FE		Yes		Yes		Yes
Observations	5,316	3,996	5,570	4,170	5,568	4,166
R-squared	0.134	0.384	0.109	0.352	0.273	0.492

Appendix D. Loan Performance by Type

Table D2. Manager Experiences and Loan Performance, Other Measures
This table reports the effect of managers' past experience gap on the loan performance at the current branch with alternative definitions of loan performance. The sample period is 1990 – 2017. The sample includes all managers that have switched jobs in the past. The unit of observations is a manager-branch-year. Branch is defined as the combination of a bank (RSSD ID) and a county. The dependent variable in Panel A and Panel B is the branch-level annual default rate (in %) which calculated from CoreLogic Loan Performance dataset. From column (1) to (4), a mortgage loan is defined as "default" if the loan is 60 days late payments as defined by OTS, 90+ days late payments as defined by OTS, in foreclosure, or real estate owned (REO). The default rate is the number of default loans divided by the number of originated loans in each year for a bank branch. Other variable definitions are the same as in Table 2. Standard errors are double clustered by manager and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Effects of Denial Rate Experience on Loan Performance

	(1)	(2)	(3)	(4)
Dep. Var:	60-day delinquency	90+ day delinquency	Foreclosure	REO
Experience Gap, Denial Rate	-0.001*	-0.001	-0.001	0.000
($Manager - Branch$)	(0.000)	(0.001)	(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
County Past Denial Rate	Yes	Yes	Yes	Yes
Bank-Year FE	Yes	Yes	Yes	Yes
Observations	5,357	5,357	5,357	5,357
R-squared	0.528	0.685	0.823	0.788

Panel B: Effects of Interest Rate Experience on Loan Performance

	(1)	(2)	(3)	(4)
Dep. Var:	60-day delinquency	90+ day delinquency	Foreclosure	REO
Experience Gap, Interest Rate	-0.041	0.043	0.098	0.042
($Manager - Branch$)	(0.047)	(0.055)	(0.083)	(0.044)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
County Past Interest Rate	Yes	Yes	Yes	Yes
Bank-Year FE	Yes	Yes	Yes	Yes
Observations	4,934	4,934	4,934	4,934
R-squared	0.767	0.703	0.816	0.845

Appendix E. Robustness for Sampling Choices

In this section, we design a robustness check on a key sampling choice. Recall that our base analysis utilizes a manager-bank-county-year sample, where we incorporate one observation for each manager when more than one manager is identified in a bank-location. This means that the outcome variables, which are computed at the bank-location level, may be repeated for some of our observations. In these cases, our baseline estimates indicate the effect of the average experience across all managers in a bank-county. We assess whether this sampling choice could influence our findings. Specifically, we compile a bank-county-level sample, randomly choosing one manager per bank-county. We then repeat our main analysis, outlined in Equation 2, for this sample. In Table E1, we continue to find a statistically significant link between managers' experience gap with changes in branch-level outcomes. In addition, we note that the coefficients are generally larger than the ones in Table 2. This indicates that our finding is unlikely driven by the sample containing having more than one manager for some bank-locations.

Table E1. Robustness: Selecting One Manager Per Bank-County

This table reports results from a robustness analysis of Table 2. In our sample there are branches with more than one branch manager. For these branches, we first keep the branch manager with the highest seniority. For the remaining branches with multiple manager, we randomly pick one branch manager. The unit of observations is a manager-branch-year. Branch is defined as the combination of a bank (RSSD ID) and a county. The key variable of interest is *Experience Gap*, measured as the average denial (interest) rates across loan applications (loans) at the past employer of a manager minus the average denial (interest) rates at the current branch over the past three years. Panel A reports the results for denial rates. The dependent variable is the year-on-year changes in loan application denial rates at the current branch. Panel B reports results for interest rates. The dependent variable is the year-on-year changes in interest rates charged on issued loans at the current branch. Detailed variable definitions are provided in Appendix A. Control variables are defined in the same way as Table 2. Standard errors are double clustered by manager and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Denial Rate (%)

Dep. Var: Δ*Denial Rate*	(1)	(2)	(3)	(4)	(5)
Experience Gap, Denial Rate	0.084***	0.116***	0.191***	0.187***	0.119***
(*Manager – Branch*)	(0.007)	(0.013)	(0.020)	(0.020)	(0.018)
Controls			Yes	Yes	Yes
County FE			Yes	Yes	Yes
Bank FE		Yes	Yes	Yes	
Year FE		Yes	Yes	Yes	
County Past Denial Rate				Yes	Yes
Bank-Year FE					Yes
Observations	6,361	6,231	6,017	6,017	4,062
R-squared	0.019	0.105	0.208	0.210	0.467

Panel B: Interest Rate (%)

Dep. Var: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)
Experience Gap, Interest Rate	0.082***	0.017***	0.039***	0.028***	0.015***
(*Manager – Branch*)	(0.006)	(0.004)	(0.007)	(0.006)	(0.006)
Controls			Yes	Yes	Yes
County FE			Yes	Yes	Yes
Bank FE		Yes	Yes	Yes	
Year FE		Yes	Yes	Yes	
County Past Interest Rate				Yes	Yes
Bank-Year FE					Yes
Observations	5,000	4,886	4,650	4,650	3,166
R-squared	0.032	0.761	0.802	0.809	0.884

Appendix F. Robustness for Branch's Experience

In this section, we design a robustness check on a key definition for *Experience Gap*. Recall that our base analysis utilizes the average of branch's past 3-year lending outcomes as branch's past experience when constructing the key variable of interest *Experience Gap*. We assess whether this time horizon choice could influence our findings. Specifically, we use the average of branch's past 5-year lending decisions as branch's experience. We then repeat our main analysis, outlined in Equation 2, for this sample. In Table F1, we continue to find a statistically significant link between managers' experience gap with changes in branch-level outcomes.

Table F1. Robustness: Using Branch's Past 5-year Experience

This table reports results from a robustness analysis of Table 2. The sample includes branch managers that have switched from a non-manager job to branch manager. The unit of observations is a manager-branch-year. Branch is defined as the combination of a bank (RSSD ID) and a county. The key variable of interest is *Experience Gap*, measured as the average denial (interest) rates across loan applications (loans) at the past employer of a manager minus the average denial (interest) rates at the current branch over the past five years. Panel A reports the results for denial rates. The dependent variable is the year-on-year changes in loan application denial rates at the current branch. Panel B reports results for interest rates. The dependent variable is the year-on-year changes in interest rates charged on issued loans at the current branch. Detailed variable definitions are provided in Appendix A. Control variables are defined in the same way as Table 2. Standard errors are double clustered by manager and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Denial Rate (%)

Dep. Var: Δ*Denial Rate*	(1)	(2)	(3)	(4)	(5)
Experience Gap, Denial Rate	0.061***	0.065***	0.094***	0.092***	0.055***
(*Manager − Branch*)	(0.006)	(0.008)	(0.011)	(0.011)	(0.011)
Controls			Yes	Yes	Yes
County FE			Yes	Yes	Yes
Bank FE		Yes	Yes	Yes	
Year FE		Yes	Yes	Yes	
County Past Denial Rate				Yes	Yes
Bank-Year FE					Yes
Observations	8,077	7,966	7,774	7,774	6,068
R-squared	0.012	0.102	0.195	0.197	0.497

Panel B: Interest Rate (%)

Dep. Var: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)
Experience Gap, Interest Rate		0.063***	0.010***	0.017***	0.014***
0.007*					
(*Manager − Branch*)	(0.005)	(0.002)	(0.005)	(0.004)	(0.004)
Controls			Yes	Yes	Yes
County FE			Yes	Yes	Yes
Bank FE		Yes	Yes	Yes	
Year FE		Yes	Yes	Yes	
County Past Interest Rate				Yes	Yes
Bank-Year FE					Yes
Observations	6,547	6,466	6,231	6,231	4,868
R-squared	0.020	0.803	0.832	0.835	0.903