Do Local Bank Branches Shape Mortgage Origination?*

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Abstract

Can local lenders influence mortgage origination and pricing decisions? We examine the role of local bank branches and their managers in the mortgage industry. We find that the idiosyncratic, past experiences of bank branch managers regarding loan approval and pricing significantly shape the corresponding decisions at current branches. Our evidence suggests local branches exercise substantial discretion over mortgage approval, but moderate discretion over pricing. Such discretion increases with credit risk, but decreases with competition. Effects are not driven by manager "style" or the selection of bank customers. Importantly, managers' past experiences help explain the heterogeneity of monetary passthrough across branches.

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1. Introduction

In the past decades, the mortgage origination industry has seen substantial shifts in its landscape, including significant geographic expansions by large lenders (Stiroh 2010; Goetz et al. 2016; Gilje et al. 2016; D'Acunto and Rossi 2022),[1] the growth of the securitization activities (Hurst et al. 2016), the rise of FinTech lenders, and the automation of lending processes within banks (Buchak et al. 2018; Fuster et al. 2019; Berg et al. 2022; Kim et al. 2022). Collectively, these changes could pave the way for more uniform loan origination and pricing decisions, leaving little room for local lenders to influence those choices. Under this backdrop, could local lenders, such as bank branches, still exert discretion over mortgage lending decisions?

This question is of policy importance as it speaks to the geographical scope of the mortgage market. In light of the development in this market, regulators view mortgage markets as national (Amel et al. 2018) and utilize national statistics for policy enforcement.[2] Consistent with this view, academic research finds no correlation between local market conditions and mortgage lenders' pricing power (Fuster et al. 2013; Hurst et al. 2016). At the same time, mortgage approval and interest rates vary widely across borrowers and lenders beyond standard characteristics (Bhutta et al. 2022, 2024), and most borrowers do not shop mortgage rates intensively across lenders, suggesting that lenders may have some discretion. Despite the importance of this question, there is virtually no direct evidence regarding whether local bank branches exercise discretion over mortgage origination and pricing, and whether their decisions lead to systematic variation in mortgage lending across geographical areas.

We seek to answer this question by examining the role of bank branch managers. Branch managers have the highest authority in bank branches and carry out a wide range of responsibilities.[3] To highlight the role of branch authority and isolate it from

[1] As of 2019, the typical bank lender receives loan applications from four states, with the top ten lenders each originating loans in 47 states.

[2] See also Federal Reserve's announcement HERE as an example of how mortgage market concentration at the national level affects regulatory decisions.

[3] Bank branch managers oversee the daily operations of a branch, including supervising accounts,

other confounding economic factors, we track managers' experiences regarding mortgage denial and pricing during their past employment in other bank branches. We then isolate the idiosyncratic component of those experiences and examine how such experiences affect their current lending decisions. These idiosyncratic experiences, uncorrelated with borrower or bank fundamentals, should not influence lending decisions if local bank branches do not have decision authority.

If local branches do have decision power, there are several reasons why branch managers' past experiences with mortgage origination may influence branches' current lending decisions. To start, personal experiences are shown to generate profound impacts on individual expectations and risk preferences (Kuchler and Zafar 2019), which in turn affect economic decisions. Such effects are important even for sophisticated finance professionals (Malmendier and Nagel 2011; Koudijs and Voth 2016; Dittmar and Duchin 2016; Malmendier et al. 2017; Carvalho et al. 2022). Additionally, bank employees often learn business practices within a branch and may apply these practices when they assume managerial roles at different branches.[4] By observing these practices, employees can build up knowledge or preferences regarding the "way of conducting business," which they carry through to the next branch.

Given the above reasons, if local branches can influence mortgage lending decisions, we should observe a link between managers' past experiences and current lending decisions. For example, having witnessed high denial rates in a previous job, a manager may consider the denial rate at the current branch to be "too low," and adjust it upwards if he has the power to do so. Our evidence supports this conjecture. Specifically, we find that bank managers' past experiences with denial rates (interest rates) significantly affect the denial rates (interest rates) at the current branch. Managers with different experiences

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. We later also examine the role of loan officers, but note that loan officers' decisions do not represent systematic variation of credit decisions across locations.

[4]Branches vary substantially in their origination procedures, including client sourcing, employee compensation, pre-screening, and customer education. While some branches adopt a more passive approach for mortgage application, others seek out customers. Branches also offer different levels of guidance to applicants than others.

also respond differently to monetary policy shocks.

To answer our research questions, 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 define a bank branch as a "local lending unit," characterized by the combination of a bank-county.[5] 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. We focus on a set of 5,713 managers who have switched jobs across bank-counties in our sample spanning from 1990 to 2017.

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. Past experiences are measured as the average rates issued by the manager's previous branch over the course of his employment. A high experience gap suggests that the manager has experienced more conservative lending decisions during his past job compared to the recent norm at the current branch. Thus, managers with high experience gaps should increase denial rates and interest rates at the current branch. Consistent with this conjecture, we find a significant, positive relation between managers' experience gaps regarding denial (interest) rates and the changes in denial (interest) rates at the new branch. Our estimation fixes a branch and tracks the changes in denial rates and interest rates over time. In stricter specifications, we further impose bank-by-year or bank-by-state-by-year fixed effects to purge out any changes in bank-region level conditions and compare how credit decisions change differently across branches of the same bank in the same state according to their managers' past experiences.

Our estimates suggest that local branches have substantial influence over mortgage origination decisions, and moderate influence over mortgage pricing. A one-standard-deviation increase in managers' experience gap for denial rates is associated with a 2.7-

[5] This classification is motivated by our data structure and availability. Standard mortgage databases only provide the lender and the location of the loan without identifying the specific branch. In cases where multiple branches of the same bank are located in the same county, our approach essentially estimates the average effects across their managers.

percentage-point increase in denial rate after the manager joins the bank. This increase accounts for 22% of the standard deviation of the annual changes in denial rates. In contrast, a one-standard-deviation increase in the experience gap regarding interest rates leads to a 2.9 basis point increase in interest rates, a 5.3% change relative to the sample standard deviation.

To the extent that managers possess unique human capital to supervise employees and implement bank-level lending policies, banks may select managers with certain "styles" or backgrounds to execute planned policy changes at their branches. While this argument still requires managers to have decision power, it suggests a different interpretation of our results. Several findings help address this concern. First, our results survive the addition of manager fixed effects. Second, we do not find managers' experience gap to be correlated with the default rates or borrowers' risk profiles at the current branch. More importantly, our results remain unchanged when we focus on managers' prior experiences during job spans when they were *not* in management positions. These experiences represent individuals' past exposures to others' lending decisions, but not their own decisions.

These findings suggest that our manager experience effects are not entirely driven by banks selecting individuals based on observed management styles or fixed individual characteristics. Instead, our findings are consistent with a "formative memory" channel, i.e., managers' past experiences shape their perceptions regarding the appropriate business practices and lending standards, and such perceptions influence the lending decisions at their current branches. We provide several analyses to substantiate this mechanism.

First, we explore the heterogeneity of the manager experience effects and examine whether such effects become more pronounced in cases where managers are expected to have greater discretion. We start by comparing the effects of manager experiences on lending decisions that could expose lenders to higher credit risk, such as approval decisions for low-income borrowers. In such scenarios, banks not only have more incentives to delegate decisions to branches, who can collect soft information, but their lending decisions are also less constrained by uniform underwriting rules. Given that our sample is at the branch-manager level, we categorize a branch's risk exposure by the average income of its loan applicants and borrowers and the average FICO scores of originated loans over the previous year. We also measure the branch's riskiness using the past delinquency and foreclosure rates of its loans. Consistent with branch managers exerting more discretion in high-risk scenarios, we find that their past experiences indeed generate stronger effects in high-risk branches.

Additionally, we examine the role of market discipline and expect managers to have less power to influence lending when facing more competitive market forces. Consistent with this conjecture, our effects are significantly weaker in counties with more lenders present and in areas where FinTech lenders occupy a greater market share. Finally, we compare the effect of manager experiences in cases where banks potentially face higher or lower cost of delegation. To the extent that branch managers may carry biases and misaligned incentives, delegation can become costly for banks with many branches, and within banks, branches that account for a significant portion of lending volume. We find evidence consistent with this prediction.

Next, we explore the role of demographic-specific experiences. Recent literature documents that personal experiences are "domain-specific," having a particularly strong influence on beliefs within the most relevant area (Kuchler and Zafar 2019). If we are capturing the effects of managers' personal experiences, such effects should be heightened when we focus on demographic-specific experiences. For example, managers' experiences with lending to minority households may influence more strongly current lending decisions to minority households. We find evidence consistent with this conjecture. A one-standard-deviation increase in managers' denial (interest) rate experience gap, calculated exclusively using minority applicants, is associated with 5.3 percentage points (4.2 basis points) higher denial (interest) rates for minority applicants in the current branch. These magnitudes are 50–100% larger than those from the baseline analysis, where experiences are computed for all applicants and borrowers. We find a similar increase in the effects from experiences related to female applicants and borrowers. In other words, demographic-specific experiences yield stronger impacts on the current lending decisions for the corresponding demographic. This finding lends further support to the "formative memory" mechanism.

Managers' experiences could affect loan approval and interest rates by shaping the composition of loan applicants, or by changing the conservativeness with which they approve loans and assess borrower risk profile. To separate these explanations, we seek to impose further controls on borrower risk profile. While our previous analysis already accounted for the average characteristics of borrowers at each branch, we now repeat our analysis using an applicant/loan-level sample, applying stricter, and more granular controls over customer and loan characteristics. These controls include the interactive fixed effects between customer demographics (including age, gender, race/ethnicity and income categories), borrower credit score, and borrower leverage with each state-year indicator, as well as fixed effects for loan type and loan amount. The refined controls for customer characteristics do not diminish the effect of manager experiences, both in terms of statistical and economic significance.

Our results thus far suggest that the experiences of bank branch managers shape mortgage lending decisions, leading to cross-geographic variation in mortgage approval rates and interest rates even within the same bank and state. In the next step, we push further the implications of our findings and investigate whether branch manager experiences generate heterogeneity in the transmission of monetary policies across bank branches.

Monetary policy is a first-order determinant of bank lending decisions, and the pass-through of such policies has important consequences for households, firms, and local economic growth (Campbell 2013; Drechsler et al. 2017; Garriga et al. 2017). Our findings could shed light on how lenders' experiences amplify or mitigate monetary policy transmission, and the distributional effects of the transmission. We focus on unexpected monetary shocks constructed from the surprise component in the federal funds futures rates, because these changes are difficult for banks to predict and tailor their hiring decisions accordingly. Monetary shocks are categorized into contractionary or expansionary, according to whether the surprises in federal funds futures rates are positive or negative.

We document that mortgage lending decisions have a stronger response when the policy shocks point to directions that confirm the managers' "priors." Fixing the manager-branch pair, mortgage interest rates increase substantially more following a contractionary policy shock when managers have positive experience gaps regarding interest rates (i.e., have experienced higher interest rates), and decrease to a greater extent after an expansionary shock when managers have negative experience gaps (i.e., have experienced lower interest rates). In contrast, when managers' past experiences conflict with the direction of the monetary policy shocks, there are little or smaller changes in mortgage interest rates. Similar patterns are documented for denial rates.

In closing, we provide additional discussions regarding our baseline findings. One concern with our methodology is that the assignment of managers to local loans may be imprecise. We note this concern, while valid, should generate noise or attenuate the empirical relation between manager experiences and lending decisions. Nonetheless, we design two additional analyses to address it. Our first analysis utilizes the identities of loan officers issuing each mortgage loan. We show that loan officers' past job experiences related to denial (interest) rates affect their current denial (pricing) decisions. This is reassuring, as it suggests that our findings apply to lower-level decision makers inside banks, where individuals can be clearly mapped to their decisions. Our second analysis focuses on a restricted sample of banks with limited geographic span, where lending choices are less likely to be made at the national headquarter. Specifically, we show that our results are robust to limiting the sample to a set of banks that operate with only one state or fewer than 10 counties.

This study contributes to several strands of literature. First, we add to the discussion regarding the geographical scope of mortgage markets. In a 2018 release, the Federal Reserve states that the mortgage market is national in scope (Amel et al. 2018). Academic research also finds little relation between local market concentration and mortgage lenders' pricing power (Fuster et al. 2013), or between mortgage pricing and local default rates (Hurst et al. 2016). Our findings contribute to this discussion by showing that local bank branches can influence mortgage origination, leading to local variation in lending decisions. Our emphasis on the past experiences of branch managers further sets us apart from previous studies that primarily consider the effect of market concentration.

More broadly, our study contributes to the literature on delegated decision-making inside banking organizations. Canonical theories analyze the benefits and costs of delegation (see, Aghion and Tirole (1997), Stein (2002), among others), and many empirical studies examine the determinants of decentralized decision-making (Berger et al. 2005; Mian 2006; Canales and Nanda 2012; Drexler and Schoar 2014; Cole et al. 2015; Liberti and Petersen 2019). 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 delegated to local branches.[6] We bridge this gap in the literature and provide microlevel evidence on delegated decision-making in this market. We also show that managers' experiences matter less when delegation is costlier to the bank.

Recent studies suggest that mortgage loan officers' characteristics can affect their credit allocation (Frame et al. 2024; Huang et al. 2022). We differ from these studies in important ways. First, we focus on the cross-branch variation to infer the decision power of local bank branches, instead of emphasizing interpersonal differences within the same branch. Second, we focus on branch managers, who hold positions of greater authority and can systematically shape bank lending decisions in a locale. Thus, the variation in their prior experiences is more likely to generate regional disparities in banks' lending decisions. Third, we examine the role of time-varying manager experiences, which help us rule out fixed managerial traits. Importantly, we show that manager experiences shape the transmission of monetary shocks and the implementation of bank-level lending 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; Buchak and Jørring 2021).

Our paper is broadly related to the studying the heterogeneity in mortgage rates across ex ante similar borrowers. Studies focusing on demand-side frictions point to the

[6] Dlugosz et al. (2022) show that banks set deposit rates locally, which allows them to be more resilient to natural disasters. Drexler and Schoar (2014) documents decentralized information possessed by bank loan officers, and 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 local competition affects mortgage lenders' responses to market conditions. However, it is not clear whether such responses are determined in the headquarter of the bank or at the branch level.

lack of shopping by customers (Alexandrov and Koulayev 2018; McManus et al. 2018; Duncan 2019; Bhutta et al. 2024), and the limited financial literacy and sophistication of households Agarwal et al. (2016, 2017) as important contributing factors. On the credit supply side, recent studies discovered that banks' funding structures and advertising strategies affect mortgage rates (Buchak et al. 2024; Gurun et al. 2016). Our study extends this literature by introducing a novel supply-side factor: the personal experiences of managers at local bank branches. We document that those experiences not only influence the credit supply decisions of local lenders, but also shape monetary transmission at the branch level.

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

2. Responsibilities of Branch Managers

Bank branch managers are the core leaders of a bank branch, and are responsible for overseeing and managing the operations of the entire branch. Their responsibilities include assessing business conditions and planning business development, designing marketing strategies, attracting and retaining customers, training and assigning employees, and implementing bank-level lending policies and regulatory compliance standards, etc.[7]

Branch managers seek to enhance profitability without sacrificing the safety or liquidity of their branches. There are a number of ways in which bank branch managers can influence mortgage lending processes and decisions. To start, branch managers help design marketing strategies to attract customers. In doing so, managers need to understand the needs of local clientele and develop long-term relationships with them. They

[7]These responsibilities are documented in practitioner guides as well as job postings. See Internet Appendix IA2 for examples of job postings for bank branch managers.

also encourage employees to cross-sell banking products that include deposits, loans, and wealth management products. Managers can decide the extent to involve digital tools in marketing. For customers with lower financial sophistication, managers decide to what extent to educate customers and coach them to find the most suitable products. Thus, managers' input can influence the composition of mortgage borrowers and the specific products they take.

Facing a set of loan applications, branch managers design policies and procedures associated with loan origination, including the stringency of lending standards, the due diligence involved in loan appraisals, and the monitoring of customer account activities. These procedures also need to comply with bank-level guidance and with regulatory standards, such as anti-money-laundering and anti-fraud regulations. While branch managers delegate a large proportion of these micro activities, they set goals for these lending activities, and design incentives for employees to achieve these goals (Misra 2023). In addition, recent studies show that employees in the mortgage origination industry differ in their experience and quality, thus can deliver different performance (Frame et al. 2024; Huang et al. 2022). Managers assign employees to different tasks and establish the responsibilities of the people involved in each task. Taken together, managers' input can play a crucial role in shaping employees' motivation and performance.

Given these responsibilities, it is plausible that managers' personal experiences can systematically influence aspects of mortgage origination that require human discretion, either through their own decisions or their leadership over bank employees.

We examine the role of branch managers in influencing mortgage approval and pricing, as both decisions require human input. While various government agencies have clear documents and algorithms that guide loan origination decisions, manual underwriting is still required. In fact, for complicated loan applications, such as borrowers with short credit history and unconventional income, underwriting algorithms defer the decision to human underwriters. Another key parameter of loan origination decision comes from the appraisal of the properties, which has been shown to embed biases and errors (e.g., Weber and McMillen 2010 and Avenancio-León and Howard 2022). Mortgage pricing is not fully automated either. Mortgage rates can vary by lenders' origination costs, customers' idiosyncratic conditions and demand (Fuster et al. 2017).[8] Finally, lenders that retain servicing rights will incorporate their servicing costs into loan pricing as well. Servicing costs, in turn, depend on anticipated delinquency rates and home recovery values. Rates display greater variation for riskier loans, which are more likely to remain on lenders' balance sheets. Lenders have greater flexibility to adjust interest rates for those loans as they are less influenced by securitization costs, and may service the loans themselves.

3. Data and Sample

3.1. 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 the Home Mortgage Disclosure Act (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 Kuttner's 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.

3.2. Sample Construction

3.2.1. 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 their names, job titles, the names of the employers, the locations of the job, as

[8] As explained by Fuster et al. (2017), origination costs include the cost of employing loan officers, underwriters, and a compliance department, as well as the cost of managing pipeline risks and securitization risks.

well as the beginning and ending dates of the job span. We start with a set of individuals that ever worked as bank branch managers at some point in their careers. We then match the names of their employers to standardized bank names and identifiers (RSSDID) in the Call Report data provided by the Federal Reserve. After filtering out non-bank employers, we are left with 49,502 individuals who have worked in 26,122 bank branches. 37,483 job spans are associated with a title 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 addresses 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.[9]

3.2.2. Mortgage Loans Data

Detailed information on mortgage applications and originated loans comes from the Home Mortgage Disclosure Act (HMDA) and CoreLogic. For each application, 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 HMDA's 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.

HMDA does not contain data on interest rates charged for a mortgage prior to 2018. We supplement this information from CoreLogic.[10] To do so, we follow a similar method

[9]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 here. During the mapping process, we require one county to be matched to no more than three 5-digit zipcodes and the resident ratio of matched zipcodes are larger than 0.1. The threshold of 10 zipcode for job location roughly means that we can narrow down the location to about three counties.

[10]CoreLogic's mortgage data includes a wide range of mortgage categories, including both private-label and agency mortgages. While not covering every single loan, CoreLogic provides a comprehensive view of mortgage market trends and performance.

as outlined by DeFusco (2018) to match HMDA with CoreLogic. We start with all originated loans in HMDA and match them to home purchase, home improvement, and refinancing loans in CoreLogic data. 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 the 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 2.5 originated loans in HMDA. The average interest rate for each grid from CoreLogic data is then assigned to all HMDA loans within the same grid.

3.2.3. 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. For denial rate analysis, we use all the application data in HMDA. Matching HMDA lenders with Revelio employers by name and location leaves us with 16,985 bank-county pairs, which cover 47% of branches based on FDIC branch information. For the interest rate analysis, we focus on approved loans and arrive at 16,262 bank-county pairs.

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 who have switched jobs over the sample period because we rely on their past job spans to gauge personal experiences. This results in 21,386 manager-branch-year observations and 5,713 unique individuals. Around two-thirds of the manager-branch-year observations in this sample are related to promotions, where an individual is promoted from a non-management position to a branch manager.

Using this panel, we construct two baseline samples. The first sample focuses on the approval and denial of loan applications. We link each manager to all the loan applications filed to that branch during his job span and compute the denial rate as the percentage of applications denied for each branch-year. The second sample is designed to analyze the interest rates of originated loans. We connect each manager with the loans originated at their branch and, consequently, the average interest rates charged on those loans.[11]

The unit of observation in both samples is a manager-branch-year. We aggregate all application (loan)-level information to this panel by computing the weighted average denial rates and interest rates of loans in each branch-year, with the weights being the mortgage amount. Similarly, we calculate the weighted average for other loan-level characteristics, including the loan-to-income ratio, the percentage of various loan types (such as home purchase loans, loans sold to other institutions, conventional loans), the debt-to-income ratio, credit score, etc. In Table IA1 of the Internet Appendix, we show that our results remain largely unchanged when branch-level variables are computed through equal weighting.

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

In additional analyses, we compile two loan-level samples, a denial-rate sample and an interest-rate sample, where the unit of observation is a manager-loan pair. We construct the denial-rate sample by merging the manager's experience dataset, which links managers to bank-county pairs, to all applications filed to the same lender-county in a year. Analogously, the interest-rate sample is constructed by combining manager experiences with all loans originated by the same lender in the same county during a year. With these loan-level samples, we can impose granular controls for bank customer characteristics and loan characteristics at the loan level, instead of at the branch level. These controls include bank customers' gender, race, age, income, credit score, and loan-to-value ratio, all interacted with state and year fixed effects. They also include fixed effects for loan size quintiles and loan type (refinancing vs. new purchase). Including these refined controls helps us better separate managers' roles in reshaping branches' customer base from their roles in adjusting branch lending strictness.

[11] The denial rate sample consists of 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.

3.3. Measuring Manager Experience

We are interested in branch managers' experiences with denial rates or interest rates from previous jobs. For each manager-branch pair, we trace back the manager's previous job in other branches, and compute the average denial rates and interest rates associated with the previous branch over the years that he/she worked in that branch.

We then compare managers' past experiences, described above, with the corresponding lending policy of their current branches in the recent past. Ideally, the managers' past experiences and the branch's past lending policies should be measured over the same horizon. However, managers have varying past job spans, while there is no set "span" for a branch. We thus compute branch-level past policies over the three years preceding the manager's arrival. This is because the average manager in our sample has an average job span of 3.3 years. In later analysis, we show that results are robust if we use a 5-year window to define past branch lending standards.

We compare a manager's past experiences with the branch's past policies and define the difference as *Experience Gap*. This measure describes the extent to which the manager's experiences deviate from the previous lending policies at the current branch. Specifically, *Experience Gap* is defined as the following:

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

where R represents the 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 (manager i's current employer). The prime subscript denotes variables in the past. Specifically, $\{b', c'\}$ represents the branch where manager i was employed prior to joining the current branch. $\bar{R}_{i,b',c',t'}$ is the weighted average denial rate or interest rate at branch $\{b', c'\}$ over the time of the manager's past employment, with the weights being loan amount. $\bar{R}_{b,c,t'}$ is the weighted average denial rate or interest rate at the current branch over the past three years, also weighted by loan amount.

3.4. Summary Statistics

The average manager in our sample works in 2.61 jobs. During a typical job switch, around 14.6% of individuals switch across counties within the same bank, around 49.7% change to a different bank inside the same county, and 35.7% switch across both banks and locations.

Table 1 reports the summary statistics of the key variables used in our analysis. Panel A describes the sample for the denial rate analysis, and Panel B provides a summary of the sample for the interest rate analysis. The average (value-weighted) denial rate is around 20.7 percentage points, and the average managers' experience gap regarding denial rates is close to zero, with a standard deviation of 16 percentage points. The average mortgage rate is 4.8 percentage points, with the average year-on-year change being -16.3 basis points. Managers' experience gap regarding interest rate has an average value of 0.7 percentage points and a standard deviation of 1 percentage point.

Table 1 About Here

The two samples have comparable statistics regarding loan characteristics, including loan-to-income ratio of around 2.3–2.7, the percentage of home purchase loans of around 41–46%, and the percentage of minority (female) borrowers of around 16–19% (25–26%). Around 54–56% of loans are applied with a coborrower.

4. Manager Experience and Mortgage Origination

We examine the relation between manager experience gaps (defined in Equation 1) and the changes in denial rates and interest rates at their current 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 the denial rates of loan applications or the 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 GSE or FHA loans, and the percentage of loans for home purchases. Borrower characteristics include the percentage of loans with a coborrower, and the percentage of loans with a female or minority applicant. We also control for manager tenure at the current branch.

Our dependent variable $\Delta R_{b,c,t}$ is the year-on-year change 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, but instead 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 control for bank-year or bank-state-year fixed effects, which remove any dynamic effect of policies or conditions at the parent bank, or at the regional office level. We further include the past average denial rate (or interest rate) for all the loan applications filed in the same county over the past three years. This variable serves as a benchmark that captures the influence of local economic conditions that could predict changes in denial rates or interest rates of mortgages in the county.

Table 2 reports the main results from estimating 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 continuous control variables, including loan, borrower, and county characteristics, as well as bank fixed effects and year fixed effects. In the third column, we further include county fixed effects. We next add county past denial rates or interest rates in column (4), and impose bank-year interactive fixed effects in column (5). Finally, in column (6), we control for bank-state-year fixed effects to eliminate any confounding effects from policy changes at the regional bank office level.

TABLE 2 ABOUT HERE

Across all specifications and outcome variables, we find a strong, positive relation between branch managers' experience gap and 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 (0.160) is associated with around a 2.66 percentage points increase in denial rate at the current branch. This is an economically significant magnitude as it represents around 22% 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 (1.022) is associated with a 2.86 basis points increase in the interest rates at the current branch, a 5.3% change relative to the sample standard deviation of the 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 stricter specification in column (5), a one-standard-deviation increase in experience gap is associated with a 1.7 percentage (1.3 basis) points higher denial (interest) rate.

Overall, our results indicate that managers' past experiences 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.

5. The Matching of Managers and Branches

In this section, we discuss the possibility that our findings may capture the matching between branches and managers. Specifically, banks that hope to tighten or loosen the lending standards at certain branches may hire managers with similar experiences to implement such changes. We note that this argument does not deny that managers need to have decision power to implement bank policies. However, under this explanation, our results may not capture the influence of past experiences on manager' decisions. We address this concern in several ways. We first examine the robustness of our results with the addition of manager fixed effects, which help rule out the possibility of our results being driven by certain manager-specific personal traits. Next, we directly test the correlation between branch characteristics and manager past experiences. Finally, we examine the role of non-managerial experiences, which should not reflect individuals' management style.

5.1. Manager Fixed Effects

We repeat our baseline analyses (Equation 2), while imposing individual fixed effects to absorb any time-invariant characteristics of managers. This set of fixed effects allows us to trace how lending decisions respond to manager experiences as the same individual changes jobs over time. We present the results in Table 3. Our results survive the addition of individual fixed effects, thus ruling out the possibility that our findings are purely driven by managers' "lending style" or any personal traits. At the same time, we note that the coefficients become substantially higher. This is likely because using manager fixed effects restricts our test to a small set of individuals that have changed jobs more than once in our sample. The estimates from column (4) of Panel A suggest that a one-standard-deviation increase in *Experience Gap* regarding denial rates within a manager (0.066) is associated with 4.87 percentage points higher denial rate at the current branch, and the same increase in the experience gap regarding interest rate (0.572) leads to a 17.46 basis points increase in the interest rates at the current branch.

TABLE 3 ABOUT HERE

5.2. Branch Characteristics and Manager Experiences

To address the concern that banks might hire managers with strict lending decisions to "correct" the lax lending standards at certain branches, we directly examine the correlation between managers' experience gap and branch characteristics that indicate credit risk exposure. For risk measures, we consider borrowers' FICO scores, loan-to-value ratios, combined loan-to-value ratios, debt-to-income ratios, income, and the percentage of loans with a co-borrower at a branch (Harrison et al. 2004). We regress the branch-year averages of these variables on the experience gaps of the branch managers.

If "strict" managers are matched to lax branches, we should observe a positive correlation of manager past denial (interest) rate experiences with branches' credit risk. However, we do not observe these relationships in Table 4. Managers' experience gap exhibits insignificant correlation with all of the branch characteristics that we examine, which does not lend support to the matching hypothesis. In addition, we compute the economic magnitudes of the coefficients as the product of the standard deviation of the experience gaps and the coefficients. We report the magnitudes at the bottom of each panel. All of the correlations yield a trivial economic effect.

Table 4 About Here

5.3. Effects of Non-Manager Job Experiences

To further address the concern that managers are hired because of their past decisions at a different branch, we reconstruct the measure of managers' past experiences using only denial rates and interest rates from past *non-manager* jobs. Job switches from a non-manager position to a branch manager position account for two-thirds of job changes in our sample. These non-manager positions include financial services officer, loan officer, teller, business advisor, etc. Individuals in those positions are unlikely to have the authority to determine the lending standards at a branch. Thus, this non-managerial experience measure captures passive experiences regarding lending policies observed, but not controlled by individuals. If our findings are purely driven by managers' fixed style, we should see the effects disappear when we look at non-management experiences.

In Table 5, we find that these non-managerial experiences continue to generate a strong, positive relation with changes in the lending outcomes at current branches. The coefficients also generate economic magnitudes similar to those from our baseline analyses. These results validate our interpretation that past experiences shape managerial decisions, and that our results are unlikely to be explained by banks selecting managers with fixed characteristics or styles.

TABLE 5 ABOUT HERE

6. Dissecting Economic Mechanisms

A prominent explanation for our findings is that managers' past experiences shape their perceptions of appropriate business practices and lending standards, and such perceptions influence the lending decisions at their current branches. We provide several analyses to substantiate this mechanism.

6.1. Heterogeneity Regarding Manager Discretion

If manager experiences shape their perceptions of lending standards or business practices, such an effect should be more pronounced in cases where managers are likely to have more discretion. We thus test the heterogeneity of our effects across decisions that embody higher or lower credit risk, across markets with higher or lower competitive pressure, and across banking organizations with different structures.

In exploring the heterogeneity of managerial effects, we estimate the following model:

$$\Delta R_{b,c,t} = \beta_1 Experience\ Gap_{i,b,c,t}(R) + \beta_2 Experience\ Gap_{i,b,c,t}(R) \times Z_{b,c,t} + \beta_3 \times Z_{b,c,t} + X_{i,b,c,t} + \alpha_b + \gamma_c + \tau_t + \epsilon_{b,c,t}, \quad (3)$$

where Z represents a characteristic either at the branch level or the local market level. The regression controls for county fixed effects (γ_c), bank fixed effects (α_b), and year fixed effects (τ_t) to control for cross-county, cross-bank, and cross-time heterogeneity, corresponding to column (2) of the baseline table (Table 2).

6.1.1. Credit Risk

We first examine the role of credit risk in moderating our effects. Specifically, we investigate how the effects vary across branches with higher or lower credit risk exposures. High-risk loans are difficult to resell and securitize. Lenders should thus have stronger incentives to conduct due diligence and enhance underwriting efforts, potentially relying more on soft information (Keys et al. 2012). As the decision requires more human input, managers' idiosyncratic beliefs or business practices could influence mortgage origination to a larger extent.

We measure a branch's credit risk exposure in several ways. First, we look at the income level of applicants and borrowers at a branch, as well as the credit scores of borrowers for originated loans. This is because loans to low-income and low-credit-score borrowers are associated with higher credit risk and are more difficult to resell. In addition, we examine the default rates for originated loans at each branch, including the percentage of delinquent loans and loans in foreclosure, since these measures are directly associated with credit losses. All of these characteristics are measured at the loan level and then aggregated to the branch-year by taking a weighted average across applications and loans, with the weights being the dollar volume on each application or loan. All characteristics are lagged, measured in the year prior to the year of observation.

We estimate Equation (3), interacting each of the credit risk measures with our main variable of interest, *Experience Gap*. For the denial rate analysis, we only consider borrower income because other metrics listed above are only defined for originated loans, not loan applications.

Table 6 reports the results from this analysis. Column (1) reports the differential effects of manager experiences on denial rates across branches with high- and low-income applicants. Columns (2) through (5) examine the differential effects of manager experiences on mortgage rates according to branch borrowers' income, FICO scores, as well as delinquency and foreclosure rates. For simplicity, coefficients β_3 on the characteristic itself are not reported.

<ins>TABLE 6 ABOUT HERE</ins>

Our results suggest that the effect of managers' past experiences is more pronounced for branches with greater credit risk exposure. Such cross-sectional variation implies significant economic magnitudes. For example, our estimates from column (1) suggest that, the effect of manager experiences on denial rate changes is about 22% larger when applicant income declines by one standard deviation. The same one-standard-deviation decline in borrower income leads to a 23% greater effect of manager experiences on loan pricing.[12] The results are qualitatively similar for credit scores and ex-post default rates.

6.1.2. Market Discipline

We next investigate the role of market discipline. While managers form beliefs and preferences based on their own experiences, such beliefs and preferences may not translate into lending decisions if they follow the denial rates and pricing of other lenders in the same market. In other words, the potential competitive pressure from other lenders in the local market may discipline managers' actions and weaken their autonomy.

We assess the extent to which the effects of manager experiences vary with the presence of other lenders competing in the same local market. We define two indicators *Many Lenders* and *Many Branches*, which are equal to one if the number of banks and bank branches identified in a county in the previous year exceeds the sample median.

Panel A of Table 7 shows that managers' experiences matter less for mortgage approval and rate-setting in areas with stronger competitive market forces. The coefficient estimates on the interaction terms (*Experience Gap* × *Many Lenders* and *Experience Gap* × *Many Branches*) are statistically and economically significant.

TABLE 7 ABOUT HERE

In addition, we examine whether the competition from FinTech lenders alters the importance of bank manager experiences. FinTech lenders have gained a significant presence in the mortgage market in the past decade (Berg et al. 2022). FinTech lenders process applications quickly and rely on algorithms to determine loan approval and interest rates, providing an attractive outside option for those who face unfavorable terms due to local

[12] The differential effect for denial rate is calculated by multiplying the standard-deviation of *log(Average Income)* (0.572) by the coefficient estimate (0.064), scaled by the baseline coefficient of *Experience Gap* (0.166, from column (3), Panel A of Table 2), which is 22.05%. For interest rate, we compute the product of the standard-deviation of *log(Average Income)* (0.543) and the coefficient estimate (0.012), and divide it by the baseline coefficient estimate of *Experience Gap* (0.028, from column (3), Panel B of Table 2) = 23.27%.

branch managers' idiosyncrasies or biases.

We define FinTech lenders following the definition of Buchak et al. (2018) and Fuster et al. (2019), and compute the FinTech penetration in a local credit market (*FinTech %*) as the percentage of loans issued by FinTech lenders in a county in the previous year. *High FinTech %* is an indicator for whether the local FinTech penetration exceeds the sample median in a given year. We then regress bank branches' lending decisions on the interaction of their managers' past experience gaps and these FinTech penetration measures. Since the literature shows that FinTech lenders started growing significantly after 2010, we restrict our sample to start in year 2011. In Panel B of Table 7, we find that the effects of manager experiences on loan approval decisions are significantly weakened by the presence of FinTech lenders. For example, our estimates in column (2) suggest that in areas with higher FinTech presence, the effect of managers' experiences on denial rates falls by 0.054, around 33% of the baseline effect (column (3), Panel A of Table 2. FinTech lenders also seem to decrease local managers' influence on loan pricing, although such an effect is not statistically significant. The lack of moderating effect of FinTech lenders on loan pricing could arise from the fact that high-risk borrowers have limited access to FinTech lenders. Those borrowers may be "held up" by local banks and have to accept the mortgage rates quoted by those lenders.

6.1.3. Organizational Structure

Lastly, we examine how banks' organizational structure influences banks' delegation of mortgage lending decisions to local branches. The analysis is motivated by prior studies showing that the complexity of the organization creates room for incentive conflicts between lower- and higher-level management. Specifically, lower-level managers granted control rights may have a desire to run their own "mini empires," resulting in more significant agency conflicts and cost of coordination (Berger et al. 2005; Graham et al. 2015). Therefore, banks with more complicated structures have incentives to limit delegation to local branches and, instead, use centralized decision-making rules based on hard information.

To test this idea, we first define *Large Bank*, an indicator equal to one if the number of branches of each bank holding company is above the sample median in the previous year, and zero otherwise. A larger branch network creates room for agency conflicts, reducing the net benefit of delegation. Our results in columns (1) and (3) in Panel C of Table 7 suggest that managers working at banks with many branches exert a smaller influence on mortgage origination.

Our second analysis examines the size of the branch. As the branch size increases, any incentive conflict or personal bias will result in higher costs borne by the parent banks. Consequently, larger branches should be more likely to be scrutinized by the headquarters and receive direct guidance on their policy setting. We denote *Large Branch* as an indicator that turns to one if the dollar volume of mortgage originated by a branch exceeds the sample median for a given year and zero otherwise. Consistent with this conjecture, results in columns (2) and (4) suggest that managers' past experiences matter less for the approval and rate setting of mortgages in large branches.

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

6.2. 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.[13] Building on this view, we compute demographic-specific experiences, and examine how such experiences influence lending decisions to borrowers of the same demographic. Demographic-specific experiences are computed as the average denial rates and interest rates in a manager's past job span from only borrowers of a particular

[13] 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.

demographic group, such as white male, female, and minority (i.e., nonwhite ethnicity), respectively. These demographic-specific experiences are then related to the current lending policies for applicants (borrowers) of the same demographics. Put differently, we measure both manager previous experiences and current lending decisions (ΔR) using borrowers in the same specific demographic group.

Figure 1 reports results from this analysis. Similar to Table 2, Panel A (B) reports results for denial rates (interest rates). In each panel, we present results for all applicants (baseline), white male, female, and nonwhite, respectively. For each of these demographic groups, we show results from the specifications in column (4) of Table 2, where we control for bank, county, and year fixed effects, and county past denial rates and interest rates.

FIGURE 1 ABOUT HERE

We find *Experience Gap* carries significant, positive coefficients across both lending outcomes for all of the demographic categories. Moreover, the coefficients for female and minority groups are generally larger than our baseline estimates. A one-standard-deviation increase in the experience gap regarding denial rate for minority applicants (0.203) is associated with an around 5.3 percentage points increase in denial rate for minorities at the current branch. A same change in interest rate experience gap related to minority borrowers (1.071) is associated with an around 4.2 basis points change in the interest rates charged to minorities at the current branch. Such magnitudes are about twice as large as those from the baseline results. Taken together, our results regarding demographic-specific experiences are consistent with the idea that more relevant experiences tend to have a greater influence on current expectations and decision-making.

6.3. Changes in Customer Profile or Lending Decisions: Evidence from Loan-Level Samples

As discussed in Section 2, branch managers' experiences could influence loan approval and interest rates in various ways, such as altering employee incentives, business strategies, and technologies at the branch, or directly adjusting the lending process. Ultimately, managers could shape lending decisions either by changing the overall profile of bank customers (loan applicants and borrowers) or by changing the stringency during loan underwriting and pricing processes, or both.

While it is challenging to fully disentangle these channels, we seek to assess the importance of the "stringency" channel by imposing more refined controls of borrower and loan characteristics. Specifically, we repeat our baseline analysis using the loan-level samples described in Section 3.2.3. Given that the dependent variables Δ*Denial Rate* and Δ*Interest Rate* in the baseline analysis represent the year-on-year changes in lending decisions, we need to redefine these variables at the application (loan) level. For each loan application, we now define Δ*Denial Rate* as the difference between an indicator for whether the current application is denied and the average denial rate at the branch over the past year. For each originated loan, we define Δ*Interest Rate* as the difference between the interest rate charged on the loan and the average interest rate charged on all loans issued by the branch over the past year. When aggregated at the branch level, these outcome variables coincide with the baseline dependent variables.

We then regress Δ*Denial Rate* and Δ*Interest Rate* on the corresponding *Experience Gap* measures, while controlling for various borrower and loan characteristics at the loan-level. Figure 2 reports the results from the loan-level analysis. Panel A reports the results from the denial-rate analysis and Panel B reports results from the interest-rate analysis. For each dependent variable, we first present coefficient estimates from a parallel specification to those of the baseline analysis (i.e., Table 2). These estimates are presented with the blue dots in each panel, with the vertical lines representing 90% confidence intervals. "Spec$N$" represents the N^{th} column in the baseline result.

FIGURE 2 ABOUT HERE

For each outcome variable and specification, we next layer on refined borrower controls. For the denial-rate analysis, we include the interactive fixed effects of borrower characteristics (race, gender, and income quintile) by state and year, such as minority-state-year and female-state-year interactive fixed effects. These controls absorb dynamics that could systematically shape the access to credit and the prices for credit by minority, female, and low-income applicants/borrowers across states and time. For the interest-rate analysis, we add not only the above borrower interactive controls, but also FICO quintile-state-year, and LTV quintile-state-year interactive fixed effects, as such information is available only for originated loans. The coefficient estimates from these specifications are presented as the red dot and vertical intervals in each panel.

Finally, we control for loan characteristics, including an indicator for refinance loans and quintile indicators for loan size. These controls absorb differential lending outcomes between refinance loans and new purchase loans, as well as loans of various sizes categories. Results from adding these controls are shown in green.

Patterns in Figure 2 suggest that even with more granular and stringent controls for borrower and loan characteristics, manager experiences still play an important role in shaping lending decisions. The added controls barely change the coefficient magnitudes, suggesting that the manager experience effects we document are unlikely driven by changes in observable characteristics of bank customers or the type of loans being made. This evidence indicates that our central findings likely reflect managers' influence over the stringency of loan underwriting and pricing. In Table IA2 of the Internet Appendix, we impose manager fixed effects in the loan-level sample regressions, and continue to find that manager experiences matter for the approval and pricing of mortgages.

7. Manager Experiences and Responses to Monetary Policy Shocks

This section examines how managers' past experiences affect the way bank branches respond to monetary policies. The goal of this exercise is two-fold: first, it highlights the role of local branches in the mortgage market during critical times when important changes in lending policies need to be implemented; second, it allows us to fix a manager-branch pair prior to the policy change and trace how mortgage lending by the manager-branch pair responds over time.

Prior literature shows that monetary policies significantly affect the prices of consumer credit, including residential mortgage rates (Ausubel 1990; Kahn et al. 2005; Scharfstein and Sunderam 2016; Buchak and Jørring 2021). Our analyses focus on how branch managers influence such transmission. In particular, we focus on branch managers' idiosyncratic experiences instead of market-wide conditions, thus highlighting the importance of the "human factor" in monetary policy transmission and its distributional effects.

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 are too low, they may be more responsive to policy shocks that tighten monetary supply and raise interest rates. In contrast, they may resist policy shocks that generate downward pressure on interest rates. Following the same logic, managers with negative experience gaps may respond more strongly to monetary easing but show muted reactions to monetary tightening. 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:

$$\Delta R_{b,c,t} = \beta_1 Experience\ Gap_{i,b,c,t}(R)^{+} \times 1^{MPS>0} + \beta_2 Experience\ Gap_{i,b,c,t}(R)^{-} \times 1^{MPS>0} + \beta_3 \times Experience\ Gap_{i,b,c,t}(R)^{+} \times 1^{MPS<0} + X_{i,b,c,t} + \alpha_b + \gamma_c + \theta_i + \epsilon_{b,c,t}, \quad (4)$$

where $Experience\ Gap^{+}$ is an indicator that equals one for managers with positive interest rate experience gaps, i.e., when managers' past experiences involve interest rates that are higher than the rates at their current branches over the past three years, 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 changes in monetary policy, i.e., monetary tightening and loosening. Changes in monetary policies are constructed using the daily changes in the federal funds futures rate around FOMC announcements. We follow Kuttner (2001) and Bernanke and Kuttner (2005), who use the changes in federal funds rate futures on FOMC dates to capture the "surprise" component in the federal funds rate changes.[14] This component should be difficult for banks or managers to predict ex-ante. Positive monetary shocks represent ones that increase banks' cost of funding, and negative shocks decrease banks' funding costs. In this estimation, $\textit{Experience Gap}_{i,b,c,t}(R)^{-} \times 1^{MPS<0}$ is absorbed as the base scenario, and coefficients β_1, β_2, and β_3 represent incremental rate changes relative to that scenario.

Table 8 reports the results from the estimation of Equation (4). We include fixed effects in stages. To start, we control for bank and county fixed effects, together with all the continuous controls used in the baseline analysis. We then add manager fixed effects and finally manager-by-branch fixed effects. For each specification, we first show the results in the absorbed benchmark scenario (columns 1, 3, and 5), i.e., rate-decreasing monetary shocks combined with managers with a negative experience gap regarding interest/denial rates. We then estimate the other three scenarios relative to this benchmark (columns 2, 4, and 6).

Table 8 About Here

Our estimates in Panel A suggest that mortgage denial rates decrease by about 2–4 percentage points following monetary loosening for branches with managers that have negative experience gaps regarding denial rates. In column (2), we examine the transmission of monetary policy shocks in other scenarios, compared to column (1). We first note that the coefficient on $\textit{Experience Gap}^{+} \times 1^{MPS<0}$ is positive and significant, suggesting that managers with high denial rate experiences are less responsive to monetary loosening. We document similar effects for interest rates in column (2) of Panel B. In terms of economic magnitudes, the coefficient on $\textit{Experience Gap}^{+} \times 1^{MPS<0}$ in column (2) of Panel B is about a half ($\frac{0.170}{0.331}$) of that in the baseline case (reported in column (1) of Panel B), suggesting that managers' high-interest rate experience in the past will largely

[14] We aggregate the event day monetary policy surprises at an annual level.

mitigate the response to rate-decreasing policy changes in the branches they oversee.

Next, we examine the effect of monetary tightening. By comparing the coefficients on $Experience\ Gap^{-} \times 1^{MPS>0}$ and $Experience\ Gap^{+} \times 1^{MPS>0}$ in column (2) of Panel A, we find that managers with positive denial rate experience gaps tighten their lending decisions following monetary tightening significantly more than managers with negative denial rate gaps. The magnitude is also significant— compared with low-denial-rate managers, those who experienced high past denial rates approve 2.7 percent fewer loans following monetary tightening.

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 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 B suggests that managers with high-rate experiences raise mortgage rates by around 32 basis points ($= 0.693 - 0.372$) following rate-increasing monetary shocks.

Taken together, our results suggest that managers' prior experiences can shape their responses to monetary policy shocks. Monetary policies generate the strongest pass-through when the policies confirm the managers' priors 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 contractionary policy pushes banks to raise the interest rates, such a shock confirms her prior and she is more likely to implement such changes. The effect of monetary policies on mortgage origination thus can differ across local bank branches, depending on who oversees and implements the policies.

8. Additional Robustness and Discussion

In this section, we provide additional discussion of our findings to further shed light on economic mechanisms and to address remaining concerns.

8.1. Loan Performance

We explore the consequences of managers' experience-driven lending decisions. For example, as managers with higher denial rate experience reject more applications, does it lead to better risk control and consequently lower delinquency at the local branches?

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 ends up delinquent.

Results in Table 9 suggest that managers' past experiences are unrelated to delinquency rates. At the bottom of the table, we present the magnitudes of the effects as the product of the standard deviation of the corresponding *Experience Gap* and the coefficients in each column. We find that all coefficients are economically small, aside from being statistically insignificant. In Table IA3 of the Internet Appendix, 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 9 About Here

Recall that in Table 4, we do not find any empirical association between managers' past experiences and ex-ante borrower risk variables (i.e., FICO score, LTV, CLTV, and DTI). Therefore, it is unlikely that these managers are hired based on the need to implement specific strategic changes of lending profile. Our results in this section further confirm that managers with high experience gaps do not significantly alter the branch's risk exposure by increasing interest or denial rates. —These actions are more likely driven by managers' subjective perceptions of the appropriate stringency in origination.

8.2. Loan Officer Experiences

One concern with our analysis is that the HMDA mortgages we study may not be extended by local bank branches, but are extended by the headquarters or by branches in different counties (Favilukis and Van Nieuwerburgh 2021). This means that the denial and interest rates on those loans do not reflect decisions by their branch managers. This concern, while valid, should add noise to the data and attenuate our results. Moreover, if loan decisions are driven by dynamics at banks' national headquarters, instead of local branches, those dynamics should be absorbed by bank-year fixed effects imposed in our baseline regressions.

Nonetheless, we design two additional analyses to address this concern. Our first analysis utilizes the precise identities of loan officers issuing each mortgage loan. Starting in 2014, CoreLogic provides a unique identifier (NMLS ID) of loan officers, which we use to link the loan officer to the mortgages she issues.[15] This allows us to circumvent the intermediate steps of matching loan officers to branches, and matching loans to branches separately, thus mitigating the concern regarding imprecise matching between loans and lenders.

Since CoreLogic also provides a standardized lender code that identifies the mortgage lender, we are able to trace the career trajectories of those loan officers and pin down the banks that they worked for in the past, although not the specific branches inside a bank. With this data, we compute loan officers' past experiences related to loan pricing and approval using the average interest rates and denial rates across all the loans issued by their past employers (banks) over their job span. We thus construct *Experience Gap* for loan officers in an analogous way as for branch managers, and repeat Equation (2) for the loans issued by those officers. Table 10 reports the results. We find that loan officers' past job experiences related to denial (interest) rates affect their current denial (pricing) decisions. This result is in line with our main findings, suggesting that the personal

[15] The SAFE Act requires that all loan officer licenses and registrations be recorded in the Nationwide Multistate Licensing System (NMLS), and the NMLS assigns each loan officer a unique identifier (NMLS ID) that stays with the officer over time and across employments.

experience effects we document apply to lower-level decision makers inside banks.

Table 10 About Here

While the test utilizing loan officer identities helps validate the mechanism of personal experience effects, it does not help answer our research question regarding the geographic scope of mortgage lending. This is because we do not observe loan officers' work locations. Moreover, there are many officers working at the bank branch (the average branch-year in our sample has 7.6 loan officers), so their idiosyncratic experiences are largely diluted. Unlike branch managers, we cannot conclude that the experiences of individual loan officers lead to systematic variations in mortgage origination decisions across regions within the same bank.

Our second analysis focuses on a sample of banks with limited geographic span, since these banks are locally oriented and their mortgage credit is less likely to be extended to an area outside of their local geographic span. Using this set of banks allows us to more precisely match a mortgage, based on its physical location, to a local bank branch. Specifically, in Table 11, we show that our results hold in a set of banks that operate in only one state or that have fewer than 10 counties.

Table 11 About Here

8.3. Alternative Measures of Experience Gap

Another 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. We design a robustness analysis to address this concern, where we also measure managers' experiences from the past three years.[16] This helps

[16]The key variation comes from individuals that have switched jobs during the past three years, as those that stayed in the same branch over the past three years will have the same experiences as the branch and thus zero experience gaps.

align the measurement horizon of managers' and branches' past lending experiences.

We repeat Equation (2) while constructing *Experience Gap* using managers' past three years of experiences. Table IA4 in the internet appendix reports the results. Panel A (B) reports results for changes in denial (interest) rate at the current branch. We continue to find a significant, positive relation between managers' experience gap and changes in lending policies at the current branch. In a separate exercise, we replace *Experience Gap* in our baseline tests using measures based on managers' and branches' past five years of experiences and continue to find robust results (see Table IA5 in the internet appendix).

8.4. Alternative Sample

Finally, we discuss an alternative sampling choice. Recall that in constructing our baseline sample, we consider a branch to be a bank-county pair, but do not distinguish branches within the same bank-county. While this test design reduces the possibility of incorrectly assigning loans to branches, it does add noise to the estimates, which reflect the effect of the average experiences from all managers in a bank-county. In Table IA6, we refine our sampling choices. We first note that around 60% of bank-counties in our sample have fewer than three managers, and 30% have only one manager identified. The number of managers identified in our sample correlates monotonically with the number of branches. We then perform a robustness test where we retain only one manager per bank-county. When there is more than one manager, we select the one with the highest seniority. If more than one branch manager has the same seniority for a given bank-county pair, we then randomly select one. Our results remain largely unchanged in this alternative sample.

9. Conclusion

In recent decades, the mortgage industry has undergone significant transformation, raising critical questions about the market's geographical scope and the role of local lenders in shaping lending decisions and standards. This paper addresses these questions by examining the influence of branch managers' idiosyncratic experiences on lending outcomes. Using a unique dataset that links branch managers to their career histories and branch-level lending outcomes, we uncover that managers' prior experiences with mortgage approval and pricing continue to shape their lending standards, even when they transition to new banks and locations. These effects are most pronounced when managers wield greater discretion in their decision-making and significantly influence their responses to monetary policy shocks.

The evidence we present is consistent with the view that lending decisions in the mortgage market are at least partly localized, driven not only by macroeconomic conditions but also by the individual experiences of key decision-makers. These findings underscore the importance of the "human factor" in financial decision-making, revealing how individual discretion and judgment continue to shape broader market outcomes in an era of increasing automation and centralization.

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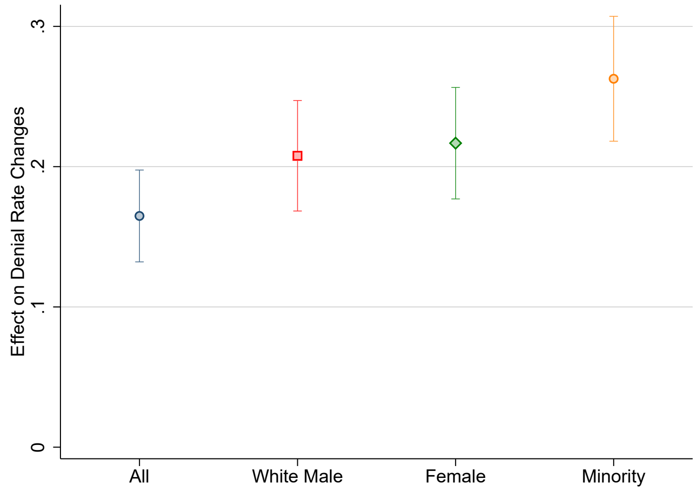
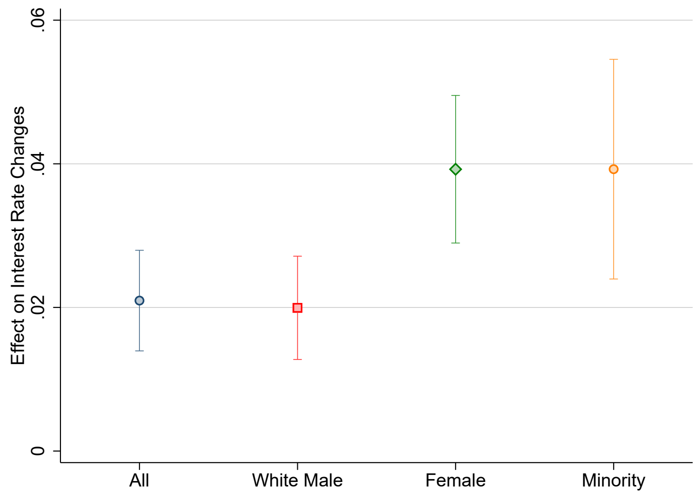
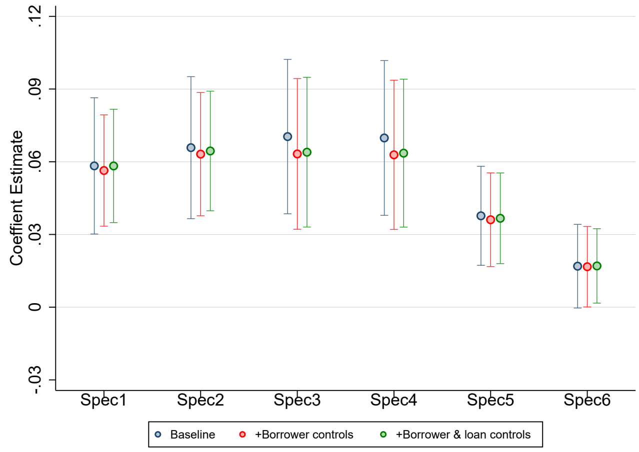


Panel A: Demographic-specific Effects on Denial Rates

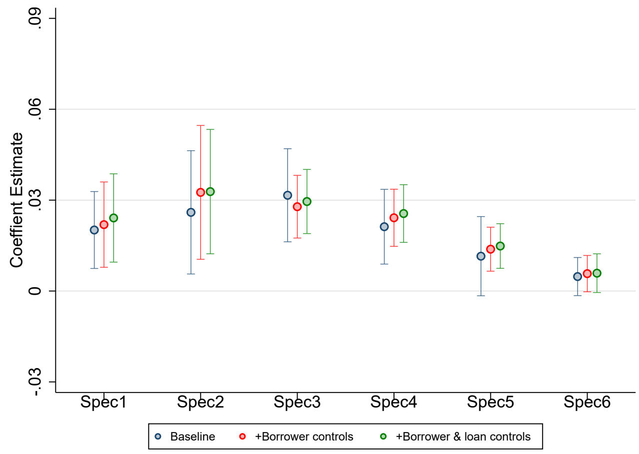


Panel B: Demographic-specific Effects on Interest Rates

Figure 1. Effects of Manager Experiences by Demographic
This figure reports the effects of manager's *Experience Gap* on the current branch's lending outcomes by separating the experiences and lending outcomes by borrower demographics. The time period is from 2000 to 2017. We look at loans to all applicants and those to white male, female, and nonwhite borrowers separately. For each group, we investigate the effects of managers' *Experience Gap*. Panel A reports the results for changes in denial rates. Panel B reports results for changes in interest rates. *Experience Gap* is measured based on past loans issued to the respective groups of borrowers only. For the results reported in Panel A and B, we include loan-level, county-level, manager-level controls as presented in Table 2, bank FE, year FE, and county FE. In each panel, the dots represent coefficient estimates and the dashed lines represent the 90% confidence interval.



Panel A: Denial Rate Analysis



Panel B: Interest Rate Analysis

Figure 2. Adding Controls for Borrower and Loan Characteristics

This figure reports the coefficient estimates of manager's *Experience Gap* when we control for additional borrower characteristics and loan characteristics using the loan-level data. The time period is from 1990 to 2017. We estimate the following loan-level model: $\Delta Y_{i,b,c,t} = \beta Experience\ Gap_{i,b,c,t}(R) + \boldsymbol{X}_i + FE + \epsilon_{i,b,c,t}$, where i represents a mortgage application (or originated mortgage), b represents a (parent) bank, c represents a county, and t represents a year. In Panel A, the dependent variable is the difference between the denial indicator for a loan and the average denial rate of the bank-county in the previous year; in Panel B, the dependent variable is the difference between the interest rate on a loan and the average interest rate of the bank-county in the previous year. *Experience Gap* is constructed as the average denial (interest) rates across loan applications (loans) of a manager's past position minus the average denial (interest) rates at the current branch over the past three years. $\boldsymbol{X}_i$ is a vector of borrower and loan controls. Borrower controls for the denial rate analysis include indicators for minority, female, having a coborrower, and income quintile in a given year. Borrower controls for the interest rate analysis additionally include credit score quintile and loan-to-value ratio quintile fixed effects. Loan controls include indicators for refinance, occupancy, and the loan amount quintile. Standard errors are clustered by county and bank. In each panel, the dots represent coefficient estimates, and the lines represent the 90% confidence interval. In *Spec1*, we only control for the refinance indicator. In *Spec2*, we add all borrower and loan controls, as well as bank and year fixed effects. In *Spec3*, we add county fixed effects. In *Spec4*, we add the control for the average of past three years' denial or interest rate of the bank-county. In *Spec5*, we add controls for bank-by-year fixed effects. In *Spec6*, we additionally control for bank-by-state-by-year fixed effects. In both panels, navy dots are based on the above mentioned specifications (i.e., "baseline"); red dots represent results from additionally interacting borrower controls with state-by-year fixed effects (such as gender-state-year, and minority-state-year interactive fixed effects); orange dots represent results from additionally interacting borrower and loan controls with state and year fixed effects (such as refinancing-state-year interactive fixed effects).

Table 1. Summary Statistics of Baseline Samples
This table presents the summary statistics for the key variables used in our baseline denial rate analysis (Panel A) and interest rate analysis (Panel B). The sample spans the period from 1990 through 2017.

Panel A: Denial Rate Sample

Variables	N	Mean	SD	P25	P50	P75
Denial rate (value-weighted)	19065	0.207	0.152	0.101	0.182	0.281
Denial rate (equal-weighted)	19065	0.246	0.161	0.130	0.224	0.333
Δ*Denial rate (value-weighted)*	19065	0.000	0.123	-0.042	0.000	0.041
Δ*Denial rate (equal-weighted)*	19065	0.002	0.107	-0.038	0.000	0.042
Experience gap (value-weighted)	19065	-0.003	0.160	-0.079	-0.004	0.061
Experience gap (equal-weighted)	19065	-0.004	0.163	-0.084	-0.004	0.064
Minority%	18998	0.190	0.179	0.069	0.142	0.250
Female%	19016	0.246	0.105	0.191	0.241	0.292
Coborrower%	19065	0.543	0.149	0.468	0.552	0.634
Loan-to-income ratio	19009	2.709	6.546	2.127	2.481	2.910
GSE/FHA%	19065	0.212	0.220	0.000	0.159	0.379
Home purchase loans%	19065	0.412	0.206	0.257	0.400	0.553
Manager tenure	19065	3.316	2.688	1.000	2.000	4.000
County past denial rate	19065	0.211	0.056	0.173	0.205	0.244
Log(County branch sum)	19065	5.119	1.105	4.394	5.247	5.829
Log(County bank sum)	19065	3.331	0.675	2.890	3.296	3.761
Log(Bank branch sum)	17189	5.704	2.036	4.043	6.397	7.326
Log(Origination)	19065	10.600	2.146	9.470	10.711	11.858
FinTech% (county-year)	19065	0.050	0.042	0.010	0.046	0.079

Panel B: Interest Rate Sample

Variables	N	Mean	SD	P25	P50	P75
Interest rate (value-weighted)	14168	4.771	1.223	3.803	4.247	5.783
Interest rate (equal-weighted)	14168	4.832	1.248	3.856	4.288	5.862
Δ*Interest rate (value-weighted)*	14168	-0.163	0.540	-0.474	-0.197	0.218
Δ*Interest rate (equal-weighted)*	14168	-0.166	0.545	-0.471	-0.209	0.237
Experience gap (value-weighted)	14168	0.732	1.022	-0.019	0.432	1.384
Experience gap (equal-weighted)	14168	0.747	1.039	-0.015	0.437	1.412
Minority%	14114	0.162	0.169	0.050	0.120	0.212
Female%	14128	0.259	0.130	0.196	0.253	0.312
Coborrower%	14168	0.562	0.166	0.471	0.566	0.662
Loan-to-income ratio	14141	2.347	0.838	2.010	2.290	2.609
GSE/FHA%	14168	0.332	0.311	0.000	0.310	0.601
Home purchase loans%	14168	0.458	0.247	0.262	0.457	0.641
Manager tenure	14168	3.275	2.583	1.000	2.000	4.000
County past interest rate	14168	5.125	1.263	3.947	4.717	6.126
Log(County branch sum)	14168	5.158	1.036	4.466	5.288	5.823
Log(County bank sum)	14168	3.339	0.648	2.890	3.296	3.714
Log(Bank branch sum)	12984	5.789	2.002	4.220	6.483	7.363
Log(Origination)	14168	9.709	2.099	8.350	9.663	10.984
FinTech% (county-year)	14168	0.046	0.043	0.000	0.040	0.076

Table 2. Manager Experiences and Lending Policies
This table reports the effect of managers' past experience gap on the changes in the denial rates and interest rates at the current branches. 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, where a branch is defined as the combination of a bank-county. The key variable of interest is *Experience Gap*, measured as the average denial (interest) rates across loan applications (loans) of a manager's past position minus the average denial (interest) rates at the current branch over the past three years. Panel A reports the results for denial rates, and Panel B reports the results for interest rates, both measured as the year-on-year changes at the branch. Detailed variable definitions are provided in Appendix A. Controls include branch characteristics (i.e., the loan-to-income ratio, % of loans that are GSE or FHA, home purchase, with a co-borrower, with a female or minority applicant), manager tenure at the branch, and the county's average denial rates or interest rates over the past three years. All branch-year-level variables are weighted averages, with loan volume as the weight. Standard errors are double clustered by bank 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)	(6)
Experience Gap, Denial Rate	0.110***	0.147***	0.166***	0.165***	0.108***	0.094***
(*Manager-Branch*)	(0.014)	(0.015)	(0.016)	(0.017)	(0.014)	(0.014)
Controls		Yes	Yes	Yes	Yes	Yes
County FE			Yes	Yes	Yes	Yes
Bank FE		Yes	Yes	Yes		
Year FE		Yes	Yes	Yes		
County Past Denial Rate				Yes	Yes	Yes
Bank-Year FE					Yes	
Bank-State-Year FE						Yes
Observations	19,065	18,884	18,819	18,819	16,110	14,557
R-squared	0.021	0.115	0.152	0.153	0.462	0.610

Panel B: Interest Rate

Dep. Var: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap, Interest Rate	0.095***	0.024***	0.028***	0.021***	0.012***	0.011***
(*Manager-Branch*)	(0.008)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
Controls		Yes	Yes	Yes	Yes	Yes
County FE			Yes	Yes	Yes	Yes
Bank FE		Yes	Yes	Yes		
Year FE		Yes	Yes	Yes		
County Past Denial Rate				Yes	Yes	Yes
Bank-Year FE					Yes	
Bank-State-Year FE						Yes
Observations	14,168	14,011	13,959	13,959	11,889	10,721
R-squared	0.032	0.769	0.777	0.784	0.883	0.913

Table 3. Robustness: Manager Fixed Effects

This table reports the effect of managers' past experience gap on the changes in the denial rates and interest rates at the current branches, while we control for manager fixed effects. 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, where a branch is defined as the combination of a bank-county. The key variable of interest is *Experience Gap*, measured as the average denial (interest) rates across loan applications (loans) of a manager's past position minus the average denial (interest) rates at the current branch over the past three years. Panel A reports the results for denial rates, and Panel B reports the results for interest rates, both measured as the year-on-year changes at the branch. Detailed variable definitions are provided in Appendix A. Controls include branch characteristics (i.e., the loan-to-income ratio, % of loans that are GSE or FHA, home purchase, with a co-borrower, with a female or minority applicant), manager tenure at the branch, and the county's average denial rates or interest rates over the past three years. All branch-year-level variables are weighted averages, with loan volume as the weight. Standard errors are double clustered by bank 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)	(6)
Experience Gap, Denial Rate	0.458***	0.642***	0.731***	0.734***	0.728***	1.018***
(*Manager* − *Branch*)	(0.056)	(0.071)	(0.073)	(0.075)	(0.109)	(0.159)
Controls		Yes	Yes	Yes	Yes	Yes
County FE			Yes	Yes	Yes	Yes
Bank FE		Yes	Yes	Yes		
Year FE		Yes	Yes	Yes		
County Past Denial Rate				Yes	Yes	Yes
Bank-Year FE					Yes	
Bank-State-Year FE						Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,047	17,904	17,933	17,933	15,093	13,503
R-squared	0.197	0.274	0.292	0.292	0.578	0.709

Panel B: Interest Rate

Dep. Var: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap, Interest Rate	0.310***	0.248***	0.362***	0.305***	0.215***	0.283**
(*Manager* − *Branch*)	(0.017)	(0.039)	(0.058)	(0.060)	(0.066)	(0.110)
Controls		Yes	Yes	Yes	Yes	Yes
County FE			Yes	Yes	Yes	Yes
Bank FE		Yes	Yes	Yes		
Year FE		Yes	Yes	Yes		
County Past Denial Rate				Yes	Yes	Yes
Bank-Year FE					Yes	
Bank-State-Year FE						Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,341	13,253	13,245	13,245	11,075	9,882
R-squared	0.302	0.792	0.798	0.800	0.894	0.921

Table 4. Manager Experiences and Ex-Ante Credit Risk
This table reports the effect of managers' past experience gap on the underwriting standards at the current branch, separated by different ex-ante measures of credit risk. 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, where a branch is defined as the combination of a bank-county. The dependent variables are the branch-year averages of ex-ante credit risk variables, including FICO score, loan-to-value ratio (LTV), combined loan-to-value ratio (CLTV), debt-to-income ratio (DTI), log of application income, and the percent of loans with co-borrowers, which are calculated as the loan-volume weighted averages at a branch in a given year. Panel A reports results for denial rate experiences. Panel B reports results for interest rate experiences. Other variable definitions are the same as in Table 2. *Effect Magnitudes* are computed as the product of the standard deviation of *Experience Gap* with the coefficients. Standard errors are double clustered by bank and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Denial Rate Experience

Dep. Var:	(1) FICO	(2) LTV	(3) CLTV	(4) DTI	(5) Income	(6) Coborr%
Experience Gap, Denial Rate	0.831	0.343	0.146	0.255	0.051	0.010
(*Manager-Branch*)	(1.214)	(0.621)	(0.611)	(0.387)	(0.036)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County Past Denial Rate	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,108	15,151	14,603	14,819	18,819	18,853
R-squared	0.711	0.660	0.595	0.429	0.735	0.621
Effect Magnitudes	0.005	0.006	0.002	0.008	0.014	0.011

Panel B: Interest Rate Experience

Dep. Var:	(1) FICO	(2) LTV	(3) CLTV	(4) DTI	(5) Income	(6) Coborr%
Experience Gap, Interest Rate	0.069	-0.002	0.025	0.007	0.004	0.000
(*Manager-Branch*)	(0.180)	(0.070)	(0.070)	(0.044)	(0.005)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County Past Denial Rate	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,945	13,965	13,657	13,788	13,959	13,965
R-squared	0.749	0.695	0.633	0.448	0.743	0.511
Effect Magnitudes	0.003	-0.000	0.003	0.001	0.007	0.002

Table 5. Non-Manager Experiences
This table reports the effect of the experiences from managers' previous non-managerial jobs on the changes in the denial rates and interest rates at the current branches. The sample period is 1990–2017. The unit of observations is a manager-branch-year, where a branch is defined as is defined as the combination of a bank-county. The key variable of interest is *Experience Gap*, measured as the average denial (interest) rates across loan applications (loans) of a manager's past position minus the average denial (interest) rates at the current branch over the past three years. Panel A reports the results for denial rates, and Panel B reports the results for interest rates, both measured as the year-on-year changes at the branch. Detailed variable definitions are provided in Appendix A. Controls include branch characteristics (i.e., the loan-to-income ratio, % of loans that are GSE or FHA, home purchase, with a co-borrower, with a female or minority applicant), manager tenure at the branch, and the county's average denial rates or interest rates over the past three years. All branch-year-level variables are weighted average with loan volume as the weight. Standard errors are double clustered by bank 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)	(6)
Experience Gap, Denial Rate	0.112***	0.164***	0.195***	0.194***	0.129***	0.121***
(*Manager-Branch*)	(0.017)	(0.021)	(0.024)	(0.024)	(0.022)	(0.026)
Controls		Yes	Yes	Yes	Yes	Yes
County FE			Yes	Yes	Yes	Yes
Bank FE		Yes	Yes	Yes		
Year FE		Yes	Yes	Yes		
County Past Denial Rate				Yes	Yes	Yes
Bank-Year FE					Yes	
Bank-State-Year FE						Yes
Observations	12,813	12,669	12,606	12,606	10,297	9,005
R-squared	0.019	0.120	0.163	0.163	0.466	0.620

Panel B: Interest Rate

Dep. Var: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap, Interest Rate	0.094***	0.026***	0.035***	0.027***	0.019***	0.019***
(*Manager-Branch*)	(0.008)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Controls		Yes	Yes	Yes	Yes	Yes
County FE			Yes	Yes	Yes	Yes
Bank FE		Yes	Yes	Yes		
Year FE		Yes	Yes	Yes		
County Past Denial Rate				Yes	Yes	Yes
Bank-Year FE					Yes	
Bank-State-Year FE						Yes
Observations	9,438	9,304	9,254	9,254	7,519	6,534
R-squared	0.031	0.759	0.768	0.776	0.881	0.911

Table 6. Manager Experience Effects and Borrower Credit Risk

This table reports the heterogeneous effects of managers' past experience gaps on the changes in denial rates and interest rates across borrower credit risks. 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, where a branch is defined as the combination of a bank-county. The key variable of interest is *Experience Gap*, measured as the average denial (interest) rates across loan applications (loans) of a manager's past position minus the average denial (interest) rates at the current branch over the past three years. The denial or interest rate is indicated at the column head. The dependent variable is either the year-on-year changes in loan application denial rates at the current branch, or the year-on-year changes in interest rates charged on issued loans at the current branch. *Log(Avg Income)* is the natural log of the weighted-average of applicant income (in thousands) for a branch in year $t-1$. *Avg FICO* is the weighted-average of borrowers' credit scores for a branch in year $t-1$. *Delinquent %* is the fraction of issued mortgages that have been 90-day delinquent for a branch in year $t-1$. *Foreclosure %* is the fraction of foreclosures of issued loans by a branch in year $t-1$. All four variables are aggregated to the branch level based on a weighted average, with the weights being the dollar amount of the loan or application. Detailed variable definitions are provided in Appendix A. Controls include branch characteristics (i.e., the loan-to-income ratio, % of loans that are GSE or FHA, home purchase, with a co-borrower, with a female or minority applicant), and the manager tenure at the branch. All branch-year-level variables are weighted averages with loan volume as the weight. Standard errors are double clustered by bank and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Dep. Var:	Δ*Denial Rate*	Δ*Interest Rate*			
	(1)	(2)	(3)	(4)	(5)
Experience Gap × *Log(Avg Income)*	-0.064***	-0.012**			
	(0.024)	(0.005)			
Experience Gap × *Avg FICO*			-0.001**		
			(0.000)		
Experience Gap × *Delinquent (%)*				-0.184***	
				(0.084)	
Experience Gap × *Foreclosure (%)*					0.100**
					(0.045)
Controls	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Bank-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	16,091	11,886	11,877	11,891	11,891
R-squared	0.442	0.882	0.886	0.882	0.881

Table 7. Heterogeneity of Manager Experience Effects
This table reports the heterogeneous effects of managers' past experience gaps on the changes in denial rates and interest rates across county and lender characteristics. The sample period is 1990–2017 except for Panel B where the sample period starts in 2011. The sample includes all managers that have switched jobs in the past. The unit of observations is a manager-branch-year, where a branch is defined as the combination of a bank-county. The key variable of interest is *Experience Gap*, measured as the average denial (interest) rates across loan applications (loans) of a manager's past position minus the average denial (interest) rates at the current branch over the past three years. The denial or interest rate is indicated at the column head. The dependent variable is either the year-on-year changes in loan application denial rates at the current branches, or the year-on-year changes in interest rates charged on issued loans at the current branches. *Many Branches* indicates whether the number of bank branches in a county exceeds the sample median in a given year. *Many Lenders* indicates whether the number of lenders in a county exceeds the sample median in a given year. *FinTech%* is the county-level fraction of annual FinTech mortgage lending to total mortgage lending, compiled by Fuster et al. (2019). *High FinTech%* indicates whether the fraction of FinTech lending over total lending in a county exceeds the sample median in a given year. *Large Bank* indicates whether the number of branches of a BHC is above the sample median in a given year. *Large Branch* indicates whether a branch's loan volume (measured by the dollar amount of originated loans) is above the sample median for a given year. Detailed variable definitions are provided in Appendix A. Controls include branch characteristics (i.e., the loan-to-income ratio, % of loans that are GSE or FHA, home purchase, with a co-borrower, with a female or minority applicant), and the manager tenure at the branch. All branch-year level variables are weighted averages with loan volume as the weight. Standard errors are double clustered by bank and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: The Role of Market Discipline

Dep. Var:	Δ*Denial Rate*		Δ*Interest Rate*	
	(1)	(2)	(3)	(4)
Experience Gap × *Many Branches*	-0.064***		-0.012***	
	(0.016)		(0.004)	
Experience Gap × *Many Lenders*		-0.043**		-0.013***
		(0.020)		(0.004)
Experience Gap	0.152***	0.134***	0.023***	0.024***
	(0.017)	(0.017)	(0.005)	(0.005)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Bank-Year FE	Yes	Yes	Yes	Yes
Observations	16,110	16,110	11,889	11,889
R-squared	0.462	0.462	0.881	0.881

Panel B: The Role of FinTech lenders

Dep. Var:	Δ*Denial Rate*		Δ*Interest Rate*	
	(1)	(2)	(3)	(4)
Experience Gap $\times$ *FinTech %*	-0.623**		0.067	
	(0.316)		(0.067)	
Experience Gap $\times$ *High FinTech %*		-0.054**		-0.000
		(0.024)		(0.004)
Experience Gap	0.126***	0.122***	0.007*	0.003
	(0.028)	(0.024)	(0.004)	(0.002)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Bank-Year FE	Yes	Yes	Yes	Yes
Observations	7,440	7,440	5,027	5,027
R-squared	0.502	0.502	0.871	0.870

Panel C: The Role of Organizational Structure

Dep. Var:	Δ*Denial Rate*		Δ*Interest Rate*	
	(1)	(2)	(3)	(4)
Experience Gap $\times$ *Large Bank*	-0.057**		0.002	
	(0.024)		(0.005)	
Experience Gap $\times$ *Large Branch*		-0.134***		-0.018***
		(0.018)		(0.006)
Experience Gap	0.150***	0.165***	0.014***	0.027***
	(0.019)	(0.015)	(0.004)	(0.008)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Bank-Year FE	Yes	Yes	Yes	Yes
Observations	14,731	11,187	11,122	8,245
R-squared	0.450	0.508	0.877	0.878

Table 8. Responses to Monetary Policy Shocks

This table reports how managers respond differently to monetary policy shocks based on their past experiences. 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, where a branch is defined as the combination of a bank-county. In this table, 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). Panel A (B) reports how the denial (interest) rates of the current branches respond to monetary policy shocks across different scenarios. $1^{MPS>0}$ 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 are higher than the current branch's level over the past three years. *Experience Gap*$^{-}$ represents negative experience gaps. The dependent variable in Panel A (B) is the year-on-year changes in denial (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 bank 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)	(6)
Experience Gap$^{-} \times 1^{MPS<0}$	-0.021***		-0.038***		-0.038***	
	(0.003)		(0.006)		(0.005)	
Experience Gap$^{+} \times 1^{MPS<0}$		0.026***		0.064***		0.068***
		(0.004)		(0.009)		(0.008)
Experience Gap$^{-} \times 1^{MPS>0}$		0.007		0.013**		0.013**
		(0.004)		(0.007)		(0.006)
Experience Gap$^{+} \times 1^{MPS>0}$		0.034***		0.071***		0.076***
		(0.004)		(0.009)		(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes		
Bank FE	Yes	Yes	Yes	Yes		
Manager FE			Yes	Yes		
Manager-Branch FE					Yes	Yes
Observations	12,342	12,342	11,391	11,391	11,115	11,115
R-squared	0.128	0.133	0.245	0.253	0.235	0.244

Panel B: Interest Rate

Dep. Var: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap$^{-} \times 1^{MPS<0}$	-0.331***		-0.485***		-0.497***	
	(0.019)		(0.028)		(0.022)	
Experience Gap$^{+} \times 1^{MPS<0}$		0.170***		0.412***		0.435***
		(0.019)		(0.036)		(0.029)
Experience Gap$^{-} \times 1^{MPS>0}$		0.424***		0.371***		0.372***
		(0.026)		(0.041)		(0.034)
Experience Gap$^{+} \times 1^{MPS>0}$		0.414***		0.668***		0.693***
		(0.023)		(0.043)		(0.033)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes		
Bank FE	Yes	Yes	Yes	Yes		
Manager FE			Yes	Yes		
Manager-Branch FE					Yes	Yes
Observations	9,141	9,141	8,369	8,369	8,174	8,174
R-squared	0.281	0.311	0.471	0.493	0.471	0.495

Table 9. Manager Experiences and Loan Performance

This table reports the effect of managers' past experience gap on the loan performance at the current branches. 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, where a branch is defined as the combination of a bank-county. The dependent variable is the branch-level annual delinquency rate (in %). A mortgage is defined as delinquent when the loan meets one of the following four conditions: (i) 60-day past due, (ii) 90-day past due, (iii) foreclosed, 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, and this average is weighted by loan volume. Other variable definitions are the same as in Table 2. *Effect Magnitudes* are calculated as the product of the standard deviation of *Experience Gap* with the coefficients. Standard errors are double clustered by bank and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Delinquency Rate and Denial Rate Gap

Dep. Var: *Delinquency Rate*	(1)	(2)	(3)	(4)
Experience Gap, Denial Rate	0.001	0.005	0.004	0.006
(*Manager-Branch*)	(0.005)	(0.006)	(0.006)	(0.005)
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes		
County FE		Yes	Yes	Yes
Year FE	Yes	Yes		
Bank-Year FE			Yes	
County Past Denial Rate		Yes	Yes	Yes
Bank-State-Year FE				Yes
Observations	15,314	15,257	12,923	11,648
R-squared	0.494	0.573	0.716	0.799
Effect Magnitudes	0.0002	0.0008	0.0007	0.0010

Panel B: Delinquency Rate and Interest Rate Gap

Dep. Var: *Delinquency Rate*	(1)	(2)	(3)	(4)
Experience Gap, Interest Rate	0.002	0.001	0.001	0.001
(*Manager-Branch*)	(0.001)	(0.001)	(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes		
County FE		Yes	Yes	Yes
Year FE	Yes	Yes		
Bank-Year FE			Yes	
County Past Denial Rate		Yes	Yes	Yes
Bank-State-Year FE				Yes
Observations	14,011	13,959	11,889	10,721
R-squared	0.547	0.624	0.755	0.842
Effect Magnitudes	0.0016	0.0011	0.0009	0.0007

Table 10. Effects of Loan Officer Experiences for Loan Pricing
This table reports the effect of loan officers' past experience gaps on the changes in the interest rates they issue. The sample period is 2014–2022. The sample includes loan officers (of commercial banks and credit unions) that have switched jobs in the past. The unit of observation is a loan. Loan officers are classified by the NMLS ID (which became available in 2014), and lenders are classified by the lender code provided by CoreLogic. The dependent variable is the difference between the interest rate on the mortgage and the volume-weighted average interest rate charged on issued loans at the current branch in the previous year, where a branch is defined as a combination of a lender and a county. The key variable of interest is *Experience Gap*, measured as the average interest rates across loans of a loan officer's past job minus the average interest rate at the current branch over the past three years. Detailed variable definitions are provided in Appendix A. Controls include the number of years the manager has served in the current position, the level and growth of county income per capita, and the growth of county population. Standard errors are double clustered by lender and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Dep. Var: Δ*Interest Rate (Loan - Branch Avg)*	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap, Interest Rate	0.126**	0.149***	0.156***	0.136***	0.263***	0.242***
	(0.057)	(0.018)	(0.016)	(0.016)	(0.030)	(0.031)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Loan Size Quintile FE	Yes	Yes	Yes	Yes	Yes	Yes
Refinance FE	Yes	Yes	Yes	Yes	Yes	Yes
Cashout Refi FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes		Yes		Yes	
Year FE	Yes					
County FE	Yes	Yes				
Bank-Year FE		Yes		Yes		Yes
County-Year FE			Yes	Yes	Yes	Yes
Loan Officer FE					Yes	Yes
Observations	742,738	740,751	758,193	756,217	748,304	746,288
R-squared	0.519	0.602	0.581	0.615	0.633	0.662

Table 11. Manager Experience Effects at Smaller Banks

This table reports the effect of managers' past experience gap on the changes in denial rates and interest rates at the current branches using a subsample of local banks. 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, where a branch is defined as the combination of a bank-county. The key variable of interest is *Experience Gap*, measured as the average denial rates across loan applications of a manager's past position minus the average denial rates at the current branch over the past three years. The dependent variable is the year-on-year changes in loan application denial rates at the current branch. Panel A reports the results for banks operating in less than 10 counties. Panel B reports the results for banks operating in only one state. Detailed variable definitions are provided in Appendix A. Controls include branch characteristics (i.e., the loan-to-income ratio, % of loans that are GSE or FHA, home purchase, with a co-borrower, with a female or minority applicant), manager tenure at the branch, and the county's average denial rates or interest rates over the past three years. All branch-year-level variables are weighted averages with loan volume as the weight. Standard errors are double clustered by bank and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Banks (<= 10 Counties)

Dep. Var: Δ*Denial Rate*	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap, Denial Rate	0.139***	0.214***	0.287***	0.285***	0.116***	0.094***
(*Manager-Branch*)	(0.016)	(0.025)	(0.032)	(0.032)	(0.017)	(0.016)
Controls		Yes	Yes	Yes	Yes	Yes
County FE			Yes	Yes	Yes	Yes
Bank FE		Yes	Yes	Yes		
Year FE		Yes	Yes	Yes		
County Past Denial Rate				Yes	Yes	Yes
Bank-Year FE					Yes	
Bank-State-Year FE						Yes
Observations	7,508	7,347	7,296	7,296	4,632	4,256
R-squared	0.025	0.145	0.196	0.197	0.681	0.724

Panel B: Single-State Banks

Dep. Var: Δ*Denial Rate*	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap, Denial Rate	0.142***	0.225***	0.304***	0.301***	0.119***	0.119***
(*Manager-Branch*)	(0.018)	(0.034)	(0.042)	(0.041)	(0.027)	(0.027)
Controls		Yes	Yes	Yes	Yes	Yes
County FE			Yes	Yes	Yes	Yes
Bank FE		Yes	Yes	Yes		
Year FE		Yes	Yes	Yes		
County Past Denial Rate				Yes	Yes	Yes
Bank-Year FE					Yes	
Bank-State-Year FE						Yes
Observations	5,475	5,323	5,292	5,292	3,032	3,032
R-squared	0.024	0.151	0.187	0.188	0.751	0.751

Internal Appendix

Appendix A. Variable Definitions

- *Denial Rate*: The average rate of loan applications being denied by a branch (bank-county) in a year, either loan volume-weighted or equal-weighted.
- Δ*Denial Rate*: Yearly change of the average rate of loan applications being denied by a branch (bank-county), either loan volume-weighted or equal-weighted.
- *Interest Rate*: The average interest rate of issued loans by a branch (bank-county) in a year, either loan volume-weighted or equal-weighted.
- Δ*Interest Rate*: Yearly change of the average interest rate of issued loans by a branch (bank-county), either loan volume-weighted or equal-weighted.
- *Experience Gap*: The average denial (interest) rates across loan applications (loans) at a manager's past position minus the average denial (interest) rates at the current branch over the past three years.
- *County Past Denial Rate*: The county's average denial rates over the past three years.
- *County Past Interest Rate*: The county's average interest rates over the past three years.
- *Manager Tenure*: Number of years a manager has been working in the current bank branch.
- *Loan-to-Income*: The ratio of loan amount and loan applicant's income for each loan application.
- *%GSE/FHA*: For all originated loans approved by a bank branch in a year, the percentage of loans being sold to Fannie Mae, Freddie Mac (i.e., the government-sponsored enterprises), or Ginnie Mae that sponsors FHA loans.
- *%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.
- *%Minority Applicants*: The percentage of minority applicants (i.e., non-white) over total mortgage applicants in a region.
- *%Female Applicants*: The percentage of female applicants over total mortgage applicants in a region.
- *%Coborrower*: The percentage of applicants with a coborrower over total mortgage applicants in a region.
- *Applicant Income*: Borrower's income at the time of application reported in the HMDA data (in thousands).
- *FICO*: Borrower's FICO credit score at the time of origination used for underwriting.
- *Loan-to-Value (LTV)*: Original Loan To Value. Original mortgage amount divided by the lesser of the origination appraised value or the sales price.
- *Combined Loan-to-Value (CLTV)*: The ratio of the total amount of debt secured by the property to the value of the property.
- *Debt-to-Income (DTI)*: 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).

- *Log(Avg Income)*: The natural log of the weighted-average of applicant income (in thousands) for a branch (bank-county) in a given year.
- *Avg FICO*: The loan-volume weighted-average of borrowers' credit scores for a branch (bank-county) in a given year.
- *Delinquent %* is the fraction of issued mortgages that have been 90-day delinquent for a branch (bank-county) in a given year.
- *Foreclosure %* is the fraction of issued mortgages that have been foreclosed for a branch (bank-county) in a given year.
- *Many Branches*: An indicator that equals one if the number of bank branches in a county exceeds the sample median in a given year.
- *Many Lenders*: An indicator that equals one if the number of lenders in a county exceeds the sample median in a given year.
- *FinTech%*: The county-level annual FinTech mortgage lending and total mortgage lending compiled by Fuster et al. (2019).
- *High FinTech%*: An indicator that equals one if the fraction of FinTech lending over total lending in a county exceeds the sample median in a given year.
- *Large Bank*: An indicator that equals one if the number of branches of a BHC is above the sample median in a given year.
- *Large Branch*: An indicator that equals one if a branch's loan volume (measured by the dollar amount of originated loans) is above the sample median for a given year.
- *Population Growth*: The county-level growth rate of total population in a year.
- *County Income p.c.*: The county-level income per capita in a year.
- *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.
- *Delinquent Rate*: The number of delinquent loans divided by the number of originated loans in each year for a bank branch. 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).

Internet Appendix

A supplementary section of the paper

"*Do Local Bank Branches Shape Mortgage Origination?*"

that is only published online

IA1. Additional Robustness Checks

Table IA1. Robustness: Equal-Weighted Averages

This table reports results from a robustness analysis of Table 2 using the loan count to calculated branch-year-level averages. 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, where a branch is defined as the combination of a bank-county. The key variable of interest is *Experience Gap*, measured as the average denial (interest) rates across loan applications (loans) of a manager's past position minus the average denial (interest) rates at the current branch over the past three years. Panel A reports the results for denial rates, and Panel B reports results for interest rates, both measured as the year-on-year changes at the branch. Detailed variable definitions are provided in Appendix A. Control variables are defined in the same way as Table 2 except that all branch-year level variables are equal-weighted averages. *, **, 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)	(6)
Experience Gap, Denial Rate	0.091***	0.124***	0.141***	0.139***	0.083***	0.067***
(*Manager-Branch*)	(0.011)	(0.011)	(0.012)	(0.012)	(0.009)	(0.008)
Controls		Yes	Yes	Yes	Yes	Yes
County FE			Yes	Yes	Yes	Yes
Bank FE		Yes	Yes	Yes		
Year FE		Yes	Yes	Yes		
County Past Denial Rate				Yes	Yes	Yes
Bank-Year FE					Yes	
Bank-State-Year FE						Yes
Observations	19,065	18,884	18,819	18,819	16,110	14,557
R-squared	0.020	0.133	0.174	0.176	0.498	0.667

Panel B: Interest Rate

Dep. Var: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap, Interest Rate	0.094***	0.021***	0.024***	0.018***	0.010***	0.009***
(*Manager-Branch*)	(0.008)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Controls		Yes	Yes	Yes	Yes	Yes
County FE			Yes	Yes	Yes	Yes
Bank FE		Yes	Yes	Yes		
Year FE		Yes	Yes	Yes		
County Past Denial Rate				Yes	Yes	Yes
Bank-Year FE					Yes	
Bank-State-Year FE						Yes
Observations	14,168	14,011	13,959	13,959	11,889	10,721
R-squared	0.032	0.792	0.800	0.806	0.901	0.925

Table IA2. Manager Fixed Effects: Loan-level Data
This table reports the loan-level estimate of the effect of managers' past experience gap on the changes in the denial rates and interest rates at the current branch, while we control for manager fixed effects. The sample period is 1990 – 2017. The sample includes all managers that have switched jobs in the past. The unit of observations is a mortgage application in Panel A and an issued mortgage in Panel B. In Panel A, the dependent variable is the difference between the denial indicator and the average denial rate of a branch in the past year, where the branch is defined as the combination of a bank-county. In Panel B, the dependent variable is the difference between the mortgage interest rate and the average interest rate of a branch in the past year, where the branch is again defined as the combination of a bank-county. The key variable of interest is *Experience Gap*, measured as the average denial (interest) rates across loan applications (loans) of a manager's past position minus the average denial (interest) rates at the current branch over the past three years. Detailed variable definitions are provided in Appendix A. Controls include indicator variables for whether the applicant has a co-borrower and whether the property is owner-occupied, manager tenure at the branch, and the county's average denial rates or interest rates over the past three years. All branch-year level variables are weighted average with loan volume as the weight. Standard errors are double clustered by bank 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	0.562***	0.566***	0.548***	0.434***	0.591***
(*Manager-Branch*)	(0.056)	(0.057)	(0.101)	(0.112)	(0.058)
Controls	Yes	Yes	Yes	Yes	Yes
County Past Denial rate		Yes	Yes	Yes	Yes
Income grid (5)-State-Year FE	Yes	Yes	Yes	Yes	Yes
Minority-State-Year FE	Yes	Yes	Yes	Yes	Yes
Female-State-Year FE	Yes	Yes	Yes	Yes	Yes
Refinance	Yes	Yes	Yes	Yes	Yes
Loan amount grid (5) FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes			
County FE	Yes	Yes	Yes		
Year FE	Yes	Yes			Yes
Bank-Year FE			Yes		
Bank-State-Year FE				Yes	
Manager FE	Yes	Yes	Yes	Yes	Yes
Branch FE					Yes
Observations	1,783,171	1,783,171	1,783,024	1,782,985	1,783,167
R-squared	0.066	0.066	0.073	0.075	0.067

Panel B: Interest Rate

Dep. Var: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)
Experience Gap, Interest Rate	0.275***	0.236***	0.123***	0.077***	0.260***
(*Manager-Branch*)	(0.084)	(0.081)	(0.043)	(0.029)	(0.089)
Controls		Yes	Yes	Yes	Yes
County Past Interest rate				Yes	Yes
FICO grid (5)-State-Year FE	Yes	Yes	Yes	Yes	Yes
LTV grid (5)-State-Year FE	Yes	Yes	Yes	Yes	Yes
Income grid (5)-State-Year FE	Yes	Yes	Yes	Yes	Yes
Minority-State-Year FE	Yes	Yes	Yes	Yes	Yes
Female-State-Year FE	Yes	Yes	Yes	Yes	Yes
Refinance	Yes	Yes	Yes	Yes	Yes
Loan amount grid (5) FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes			
County FE	Yes	Yes	Yes		
Year FE	Yes	Yes			Yes
Bank-Year FE			Yes		
Bank-State-Year FE				Yes	
Manager FE	Yes	Yes	Yes	Yes	Yes
Branch FE					Yes
Observations	694,860	694,860	694,643	694,579	694,856
R-squared	0.509	0.509	0.515	0.516	0.509

Table IA3. Loan Performance by Delinquency Type
This table reports the effect of managers' past experience gap on the loan performance at the current branch, separated by different types of delinquency. 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, where a branch is defined as the combination of a bank-county. The dependent variable in Panel A and Panel B is the branch-level annual delinquency rate. In columns (2)-(4), a mortgage is defined as delinquent when the loan is 60-day past due, 90-day past due, or foreclosed, respectively. In column (1), a mortgage is defined as delinquent when the loan meets one of the above-mentioned conditions. 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, and this average is weighted by loan volume. Panel A reports results for denial rate experiences. Panel B reports results for interest rate experiences. Other variable definitions are the same as in Table 2. Standard errors are double clustered by bank and county. *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Panel A: Denial Rate Experience

Dep. Var:	(1) All	(2) 60-day delinquency	(3) 90+ day delinquency	(4) Foreclosure
Experience Gap, Denial Rate	0.005	0.005	0.008	0.006
(*Manager-Branch*)	(0.006)	(0.006)	(0.005)	(0.005)
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
County Past Denial Rate	Yes	Yes	Yes	Yes
Observations	15,150	15,150	15,150	15,150
R-squared	0.578	0.578	0.586	0.620

Panel B: Interest Rate Experience

Dep. Var:	(1) All	(2) 60-day delinquency	(3) 90+ day delinquency	(4) Foreclosure
Experience Gap, Interest Rate	0.001	0.001	0.001	0.000
(*Manager-Branch*)	(0.001)	(0.001)	(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
County Past Denial Rate	Yes	Yes	Yes	Yes
Observations	13,959	13,959	13,959	13,959
R-squared	0.624	0.624	0.638	0.664

Table IA4. Robustness: Past Three Years of Experience

This table reports results from a robustness analysis of Table 2 using the past three years to measure managers' past job experience. 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, where a branch is defined as the combination of a bank-county. The key variable of interest is *Experience Gap*, measured as the *past-three-year* average denial (interest) rates across loan applications (loans) 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, and Panel B reports results for interest rates, both measured as the year-on-year changes at the 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 bank 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)	(6)
Experience Gap, Denial Rate	0.121***	0.157***	0.178***	0.177***	0.113***	0.098***
(*Manager-Branch*)	(0.015)	(0.016)	(0.018)	(0.018)	(0.015)	(0.015)
Controls		Yes	Yes	Yes	Yes	Yes
County FE			Yes	Yes	Yes	Yes
Bank FE		Yes	Yes	Yes		
Year FE		Yes	Yes	Yes		
County Past Denial Rate				Yes	Yes	Yes
Bank-Year FE					Yes	
Bank-State-Year FE						Yes
Observations	19,034	18,851	18,787	18,787	16,080	14,526
R-squared	0.022	0.115	0.153	0.154	0.462	0.610

Panel B: Interest Rate

Dep. Var: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap, Interest Rate	0.104***	0.039***	0.047***	0.038***	0.023***	0.021***
(*Manager-Branch*)	(0.009)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
Controls		Yes	Yes	Yes	Yes	Yes
County FE			Yes	Yes	Yes	Yes
Bank FE		Yes	Yes	Yes		
Year FE		Yes	Yes	Yes		
County Past Denial Rate				Yes	Yes	Yes
Bank-Year FE					Yes	
Bank-State-Year FE						Yes
Observations	14,144	13,987	13,936	13,936	11,866	10,697
R-squared	0.027	0.769	0.777	0.785	0.884	0.914

Table IA5. Robustness: Branch's Past Five-Year Average
This table reports results from a robustness analysis of Table 2 using the past five years' average rates of a bank branch to calculate the *Experience Gap*. 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, where a branch is defined as the combination of a bank-county. The key variable of interest is *Experience Gap*, measured as the average denial (interest) rates across loan applications (loans) of a manager's past position minus the average denial (interest) rates at the current branch over the past *five* years. Panel A reports the results for denial rates, and Panel B reports results for interest rates, both measured as the year-on-year changes at the 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 bank 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)	(6)
Experience Gap, Denial Rate	0.081***	0.092***	0.104***	0.104***	0.066***	0.053***
(*Manager-Branch*)	(0.008)	(0.011)	(0.011)	(0.011)	(0.010)	(0.009)
Controls		Yes	Yes	Yes	Yes	Yes
County FE			Yes	Yes	Yes	Yes
Bank FE		Yes	Yes	Yes		
Year FE		Yes	Yes	Yes		
County Past Denial Rate				Yes	Yes	Yes
Bank-Year FE					Yes	
Bank-State-Year FE						Yes
Observations	17,265	17,107	17,046	17,046	14,717	13,375
R-squared	0.011	0.089	0.128	0.129	0.459	0.611

Panel B: Interest Rate

Dep. Var: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap, Interest Rate	0.055***	0.014***	0.013***	0.009***	0.005**	0.003*
(*Manager-Branch*)	(0.006)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Controls		Yes	Yes	Yes	Yes	Yes
County FE			Yes	Yes	Yes	Yes
Bank FE		Yes	Yes	Yes		
Year FE		Yes	Yes	Yes		
County Past Denial Rate				Yes	Yes	Yes
Bank-Year FE					Yes	
Bank-State-Year FE						Yes
Observations	12,517	12,379	12,326	12,326	10,593	9,584
R-squared	0.010	0.792	0.805	0.814	0.907	0.936

Table IA6. Robustness: Selecting One Manager Per Bank-County
This table reports results from a robustness analysis of Table 2 where we retain only one manager per bank-county. In bank-county pairs where there are more than one branch managers identified, we select the one with the highest seniority. If more than one branch managers have the same seniority for a given bank-county pair, we then randomly select one. 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, where a branch is defined as the combination of a bank-county. The key variable of interest is *Experience Gap*, measured as the average denial (interest) rates across loan applications (loans) of a manager's past position minus the average denial (interest) rates at the current branch over the past three years. Panel A reports the results for denial rates, and Panel B reports results for interest rates, both measured as the year-on-year changes at the 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 bank 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)	(6)
Experience Gap, Denial Rate	0.117***	0.143***	0.155***	0.154***	0.112***	0.103***
(*Manager-Branch*)	(0.016)	(0.016)	(0.017)	(0.017)	(0.016)	(0.014)
Controls		Yes	Yes	Yes	Yes	Yes
County FE			Yes	Yes	Yes	Yes
Bank FE		Yes	Yes	Yes		
Year FE		Yes	Yes	Yes		
County Past Denial Rate				Yes	Yes	Yes
Bank-Year FE					Yes	
Bank-State-Year FE						Yes
Observations	10,053	9,877	9,804	9,804	7,446	5,928
R-squared	0.021	0.117	0.172	0.173	0.445	0.586

Panel B: Interest Rate

Dep. Var: Δ*Interest Rate*	(1)	(2)	(3)	(4)	(5)	(6)
Experience Gap, Interest Rate	0.096***	0.026***	0.032***	0.025***	0.015***	0.014***
(*Manager-Branch*)	(0.007)	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)
Controls		Yes	Yes	Yes	Yes	Yes
County FE			Yes	Yes	Yes	Yes
Bank FE		Yes	Yes	Yes		
Year FE		Yes	Yes	Yes		
County Past Denial Rate				Yes	Yes	Yes
Bank-Year FE					Yes	
Bank-State-Year FE						Yes
Observations	10,656	10,499	10,442	10,442	8,120	6,784
R-squared	0.031	0.751	0.759	0.766	0.857	0.884

IA2. Job Postings for Bank Branch Managers

Example 1: United Bank
Job description: This Branch Manager opportunity will be responsible for managing the functions of a full service branch, including maintaining existing and developing new customer relationships, both personal and business. The Branch deposit size is normally under $25,000,000. Accountability includes achieving sales performance objectives of the branch relating to deposit growth, fee income, and expense control. Responsible for the supervising, coaching, and developing of branch staff and ensuring the communication and adherence with all Bank best practices, policies, procedures, and regulations.

Selected responsibilities:

- Leads by example and proactively builds existing retail and business customer relationships and develops new consumer relationships
- Achieves sales performance goals and objectives relating to, deposit growth, investment and fee income, and cost control
- Manages and coaches the branch sales team to effectively provide financial solutions to customers
- Has knowledge of and complies with Bank security and operating policies and procedures, as well as compliance regulations including KYC, OFAC, CIP, and Information Security policies and procedures
- Coordinates with Regional Managers and Human Resources on the hiring of new employees, performance reviews, employee discipline, terminations and salary adjustments
- Takes responsibility in meeting monthly branch and/or individual scorecard sales goals on a consistent basis by monitoring self-performance and following action plans

Example 2: CapitalOne
Job description: The Branch Manager provides supervision and guidance to staff, coaching and developing employees. They ensure that branch activity drives overall profitability of the branch and meets credit union goals and objectives. This position also oversees ATM balancing and operation. The role assists as needed with member service coverage, modeling exceptional member service. They assure that credit union policies and procedures are followed. Maintains equipment and files necessary to keep accurate records.

Selected responsibilities:

- Maintain knowledge of all credit union services to support cross-selling to all members and training and guidance to staff.
- Provide training, assistance and supervision to staff, assist with complex transactions and error correction. Delegate back-office work and specialized project assignments as necessary.
- Resolve member problems and unusual situations in the teller and member services areas as needed.
- Implement procedural and policy changes as requested by management.
- Review and recommend changes/ updates to internal policies and procedures necessary to maintain efficient and accurate customer service.

- Comply and follow Bank Secrecy Act regulations.

Example 3: PNC Financial
Job description:

- Responsible for leading all aspects of branch performance. Drives revenue and customer loyalty through consultative interactions with clients, and solutions that help them achieve financial well being. Creates a differentiated customer experience, making banking easy in an omni channel environment. Collaborates with a broad range of eco-system partners. Accountable for risk management and compliance. Builds a high performing team through the attraction, on-boarding, coaching and development of branch team members.

Example 4: Truist Bank
Job description: The Branch Leader has responsibility for managing all aspects of assigned Branch(es). The responsibilities include but are not limited to: Driving Branch Performance through Leading, Coaching and Managing and Business Development. Small Business Expertise and Development critical to Truist Purpose in inspiring and building better lives and communities. Ensuring compliance with internal controls, operational procedures and risk management policies. Management of Human Capital including interviewing, selection, hiring, conducting performance reviews, disciplinary actions, workforce management scheduling.

Selected Responsibilities:

- Drive the Business Development of the branch to deliver both strong team performance as well as strong individual performance through personal productivity, in the areas of Truist strategy including but not limited to Small Business, Mass Affluent, Work Financial Wellness, and Integrated Relationship Management (IRM) partnership.
- Drive branch revenue through Small Business development and new client strategies. Drive the growth of Small Business expertise through branch routines of face to face appointments with clients, outbound calling, and prospecting as well as the growth of Mass Affluent through face to face appointments and outbound calling.
- Participation as reviewed and approved in the Market, in civic, government, professional, business, community affairs, associations and groups to prospect and develop new business through community involvement and build the Brand.
- Responsible for successfully executing on the Branch Engagement Routines by leading, growing, coaching and motivating teammates, to fulfill the Purpose Mission and Values for client's financial success and team empowerment. Proactively engage consumer and small business client base through effective outbound calling and OnUp outreach.
- Responsible for Human Capital decisions including interviewing, selection, hiring, workforce scheduling, development planning, annual performance reviews, ratings, and performance counseling including disciplinary actions for all members of branch team.